Learning and the Value of Information:
The Case of Health Plan Report Cards

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Michael Chernew#
Department of Health Management & Policy
Department of Economics
Department of Internal Medicine
The University of Michigan,
and NBER

Gautam Gowrisankaran
Department of Economics
University of Minnesota,
Federal Reserve Bank of San Francisco,
and NBER

Dennis P. Scanlon
Department of Health Policy & Administration
Center for Health Policy Research
The Pennsylvania State University

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#Corresponding Author:

Michael Chernew, Ph.D.
Associate Professor
Department of Health Management and Policy
University of Michigan
109 S. Observatory
Ann Arbor MI 48109-2029
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Abstract

We estimate a Bayesian learning model in order to assess the value of health plan performance information and the extent to which the explicit provision of information about product quality alters consumer behavior. We take advantage of a natural experiment in which health plan performance information for HMOs was released to employees of a Fortune 50 company for the first time. Our empirical work indicates that the release of information affected health plan choices. Consumers were willing to pay an extra $276 per year per below average rating avoided, and the average value of the information per employee was $22 per year. The priors on quality and the quality ratings have a correlation of 0.14 that is statistically significant. The results suggest that despite the existence of a variety of informal mechanisms to convey information, including reputation, consumers may value formally constructed performance measures.

Keywords: Information, Uncertainty, Health Plan Choice, Health Plan Quality, Managed Care.

JEL Classification: I11
I. Introduction

In many markets products vary substantively in terms of quality. Yet, quality is often not readily observable. In these markets, it is uncertain what information is reflected in market equilibrium. Failure of markets to capture full information may diminish welfare in a variety of ways (Stiglitz, 1989). While economic theories identify mechanisms by which firms may gain reputations regarding quality, such as informal information networks, the characteristics of information make it hard to commodify. Information is hard to value before it is known and, in many settings, has public good characteristics.

Accepting that reputation is an important attribute for many markets with quality differentiation, we seek to understand the impact of formally provided information on consumer behavior. In this paper we examine the impact of report-card information in the market for health insurance plans. We make use of a natural experiment where information on the performance of managed care health insurance plans was released, and estimate a Bayesian learning model that quantifies the prior information from reputation as well as the information from the report-card ratings.

By doing so, we are able to estimate the value of formally constructed and disseminated information and can assess the extent to which consumers’ prior beliefs regarding quality correspond to the formally provided signals of quality. As with all natural experiments, our estimated results directly reveal only values for the experiment that we are examining. If we were to find no consumer response to information, we could not determine if this were due to lack of information imperfections ex-ante or due to poorly constructed and disseminated ratings. Nonetheless, we feel that our results are of interest because they provide both direct evidence on

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1 For example, Arrow (1963) comments on the ‘elusive character’ of information as a commodity.
the value of information for the health care sector and indirect evidence that may be applicable to other sectors of the economy.

Understanding the role of information in the health insurance sector is particularly important since the sector is notoriously plagued by a variety of information imperfections (Arrow, 1963). In particular, quality is an important attribute in health care markets and hard to verify. Moreover, over the past three decades there has been an increasing reliance on market mechanisms to allocate health care resources. The rise of the market system has caused a concurrent increase in the demand for information about the quality of health plans and health care providers.

The demand for information is particularly important for managed care health plans. Managed care plans provide a mechanism for individuals to commit to a package of benefits and style of care before they realize their illness shock. Individuals can maximize their utility by selecting health plans that provide a desired combination of premium and quality. Yet optimal choice of health plans also requires information about the nature of care provided by each plan.

The increasing reliance on managed care is not without controversy. The popular press has widely portrayed the quality of care in managed care plans as substandard, despite evidence that outcomes, in general, are comparable (Miller and Luft, 1994). Public complaints and controversy about the quality of care have been widespread and spawned legislative efforts such as patients’ bills of rights. Advocates of managed care have thus recognized the widespread need to provide consumers with information about plan performance. Starting in the mid 1990s, the demand for information has given rise to a burgeoning industry to measure and report health plan performance to consumers. Many organizations, including the Federal Employees Health Benefit
Program (FEHBP) and the federal Medicare program, as well as some large firms, use measures of plan performance to create health plan report cards.

Our particular focus is on quantifying the extent to which these report cards influence health plan choice and using the observed reaction to report cards to infer the implied value of report card information to employees. Our analysis is based on a natural experiment in the health insurance market in which the General Motors Corporation (GM) started providing formal ratings of health maintenance organization (HMO) managed care health plans to its salaried employees. We observe a large sample of health plans in many markets, which allows us to use plan-market specific fixed effects to identify prior reputations.

GM has been at the forefront of creating and disseminating measures of health plan performance. In 1996, the dominant form of information about plan quality was ‘reputation’, which includes a variety of informal sources of information including information from family, friends, colleagues, the news media, and even physicians. At the time, the quality reporting industry was in its infancy and there were relatively few examples of the direct provision of health plan performance information to eligible consumers.

One of the first examples involved GM, which during the 1997 open enrollment period provided salaried employees with formal evaluations of plan performance. For each offered HMO health plan, the ratings listed the performance in a variety of dimensions as being one of three levels. Ratings were not provided for traditional Fee For Service (FFS) plans or Preferred Provider Organizations (PPOs), since the data used to construct the ratings were only available for HMOs. PPOs provide employees with incentives to use network providers, but typically do not incorporate the cost control mechanisms characteristic of many HMOs.
Our results indicate a significant effect of the information on choice, suggesting that direct measurement and release of health plan performance information may be valuable. We estimate that the willingness to pay for a plan increases $276 per year if one out of six ratings on the plan were average as opposed to below average. In addition, employees seem more sensitive to negative information than positive information. This is consistent with a wide body of work on framing in decision-making and consistent with laboratory experiments investigating the role of information in health plan choice (Hibbard et al. 2000).

Because our estimates are based on an underlying utility maximization framework, the estimated coefficients can be used to understand the overall impact of the ratings on utility and health plan choice, subject to caveats discussed later. We estimate that the value created by the report card information is between $22 and $27 per GM employee per year, and that the information caused between a –0.15 and +2.60 percentage point increase in managed care enrollment. The range of values reflects alternative assumptions about the aggregate 1997 HMO enrollment in the absence of report card information. Lastly, we find that individuals were not completely ignorant of plan traits in the absence of information. The priors and the report card information had a statistically significant and positive correlation of 0.14.

This remainder of this paper proceeds as follows. The next section outlines the related literature. Section 3 specifies the learning model, identification and estimation. Section 4 details the natural experiment and data. Section 5 provides results. Section 6 concludes.

II. Literature

Many theoretical models of imperfect or asymmetric information examine the consequences of the information structure on equilibrium outcomes. Models in this literature
illustrate signaling behavior (Spence, 1973), and lack of equilibrium or incomplete markets (Rothschild and Stiglitz, 1976; Akerlof, 1970)). Even when equilibrium exists, many studies have shown that prices will be higher than marginal costs and that if prices signal quality then prices can be ‘sticky’.\footnote{Stiglitz (1989, p. 823, 825) provides a detailed literature review.}

A recent body of empirical work assesses the extent to which consumers learn from information (Ackerberg, 2001; Crawford and Shum, 2000, Milyo and Waldfogel, 1999). These studies conclude that consumers learn from experience and from advertising signals. Low-cost availability of information may lead to equilibrium outcomes that are close to the full information equilibrium outcomes (Jin and Leslie 2001). Our focus is not on characterizing equilibrium outcomes in the face of information imperfections. Instead, similar to the work by Ackerberg and by Crawford and Shum, we examine one part of the puzzle in detail, the impact of information on consumer behavior.

Studies of information in health care markets suggest that reputations exist but that individuals do not feel fully informed (Luft et al., 1990; Chernew, Scanlon and Hayward, 1998; Hibbard and Jewett, 1996; Hibbard et al. 2000; Robinson and Brodie 1997; and Tumlinson et al. 1997). Most recent studies of health plan choice have examined the role of price, but not quality (Buchmueller and Feldstein, 1997; Cutler and Reber, 1996; Royalty and Solomon, 1999). However, two studies examine the impact of report cards on plan choice (Scanlon et al., 2002; Wedig and Tai-Seale, 2001). Both find a response to the information. Neither directly measures the value of information to consumers.
III. Model and Estimation

Model

We postulate a Bayesian learning model where consumers learn about health plan quality. In our framework, individuals select a health plan from a menu of plans in order to maximize their expected utility. The expected utility of a plan is a function of the price charged to employees for joining, the benefits covered, and the perceived quality. Quality is multidimensional, incorporating perceived aspects of convenience, quality of providers, and customer service. At any time period, a consumer will perceive some distribution for the quality of each plan. The perception of quality is a function of reputation (including informal information), direct information about performance, and observable plan attributes. We view health plan report cards as a potential source of information about performance that serves to update consumers’ beliefs about plan quality.

We consider a simple model where individual ‘i’ resides in market ‘m’ at time period ‘t’, and must choose among a set of plans ‘j’. Individuals care about the perceived plan quality, $q_j$, which is expressed in utility units. Thus, the expected utility function for an individual at time $t$ is given by:

\[ u_{ijmt} = E_{ijmt} \left[ q_j \right] - \alpha_{jmt} P + \sigma_{ijmt} \epsilon_{ijmt}, \]

where ‘$E$’ is a conditional expectation given the available information, ‘$P$’ is price, ‘$\alpha$’ and ‘$\sigma$’ are parameters, and ‘$\epsilon$’ is a component of utility that is not systematically related to plan quality and is unobservable to the econometrician.

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 and we do not have to consider strategies in which consumers sample plans in a dynamic context. Because we do not believe that ‘sampling’ plans is a common strategy, we do not consider this assumption particularly restrictive. We let the unobservable \( \varepsilon_{ijmt} \) be distributed with a Type I extreme value distribution as this is the distribution that leads to logit shares.

In some specifications, we allow for correlated \( \varepsilon \)'s for plans of the same type, using the nested logit specification of Cardell (1997) and Berry (1994). Following these papers, we let

\[
e_{ijmt} = e'_{ig(j)mt} + \lambda e''_{ijmt},
\]

where \( e' \) and \( e'' \) are independent, \( \lambda \) is a parameter to estimate, \( g(j) \) indexes the plan type of plan \( j \) (i.e. HMO, PPO and FFS), \( e'' \) is distributed extreme value, and \( e' \sim C(\lambda) \), defined as the unique distribution that makes \( e \) extreme value given \( \lambda \) and the distribution of \( e'' \). If \( \lambda = 1 \), then the model will be identical to the logit model and the unobservables will be iid, while if \( \lambda = 0 \), the unobservables will be perfectly correlated within a group. The nested logit model is very useful because it provides a natural way to quantify the extent to which consumers are willing to switch between types of plans, and for our purposes it is important to understand the extent to which ratings cause consumers to switch from FFS plans to HMOs.

We consider individuals at two time periods, 0 and 1. Signals, in the form of health plan report cards, are given to individuals immediately before they make their choice of health plan at time 1. Thus, the conditional distribution of quality at time 0 (i.e. the prior) is a function solely of reputation, while the conditional distribution of quality at time 1 (i.e. the posterior) is a function of both reputation and the signal. For analytic ease, we assume that the priors and signals are normally distributed. We let the prior, \( q_{ijm,0} \), be distributed
and let the signal derived from the quality report card be distributed around the true perceived quality as:

\[(4) \quad s_{jm} \sim N(q_j, h^{-1}_2),\]

where \(h_1\) and \(h_2\) are precisions of the priors and signal respectively. We assume that the priors and signals are uncorrelated across plans in a market. We let the signal \(s_{jm}\) be related to the published ratings \(r_j\), as

\[(5) \quad s_{jm} = \beta r_j + \sigma \nu v_{ijm},\]

where \(\beta\) and \(\sigma\) are parameters and \(v_{ijm} \sim N(0,1)\) captures time varying plan level traits that might relate to perceived quality and are observed to the individuals but not to the econometrician. This variable captures factors such as changing provider networks or positive media coverage. We note that the assumption that the signal is normally distributed is an approximation. In reality, the signals will have some complex distribution, based on the distribution of the \(r_j\)'s conditional on true quality. However, we think that any bias from the normal approximation will be small.

Given this specification, we can derive the conditional expectation of quality at time 0 and 1. From (3), the prior mean is \(E_{q_{jm0}}[q_j] = \bar{q}_{jm}\). Using (3) – (5) in conjunction with standard Bayesian updating formulas, we obtain a posterior mean of

\[(6) \quad E_{q_{jm1}}[q_j] = \frac{h_1 \bar{q}_{jm} + h_2 (\beta r_j + \sigma \nu v_{ijm})}{h_1 + h_2}.\]
For our estimation process, we estimate each prior mean on quality, $\bar{q}_{jm}$, as a separate parameter. We choose this specification because, in keeping with the natural experiment, we want to identify the effect of the ratings separately from any prior on plan quality. Moreover, these parameters may differ across markets for the same plan, because of the local nature of physician and hospital networks.

**Identification**

Although we have fully specified the model, we have not yet discussed identification. As with discrete choice utility models, we can identify the coefficients only up to a factor of proportionality. Thus, we normalize $\sigma_e = 1$. Similarly, we need to normalize one plan to have prior quality 0 for every market. We normalize the FFSE plan to have prior mean quality 0, and call it plan 0, the reference plan, so that $q_0 = 0$. Thus, the prior mean qualities for all other plans as well as the signals for all HMOs, should be thought of as relative to the reference plan.

We choose FFSE as the reference plan for two reasons. First, it does not have published ratings. This is important, because if we had chosen an HMO as a reference plan, we would have had to modify the derivation of the posterior in (6) to account for the fact that the posterior quality is relative to this reference plan. Second, this plan is homogeneous and offered in every market. This is similarly important because it allows us to compare perceived quality levels across markets, since they will all be relative to the same plan.

There is also another identification issue that is particular to learning models: we cannot jointly identify the precisions, $h_1$ and $h_2$. The reason for this, which can be seen from examining (6), is that multiplying $h_1$ and $h_2$ by the same constant would yield the same posterior on quality and not change the prior. Thus, we normalize these two parameters by making them sum to 1.
Given this normalization, our model becomes:

\[ u_{ijmt,j=0} = \bar{q}_{jm} - \alpha P_{jm} + \epsilon_{ijmt}, \text{ if } t = 0 \text{ or } j \text{ is not an HMO} \]

\[ u_{ijmt,j=0} = -\alpha P_{jmt} + \epsilon_{i0mt}, \]

\[ u_{ijm1} = \tilde{h} q_{jm} + \tilde{r}_j + \tilde{\sigma}_v v_{ijm} - \alpha P_{jm1} + \epsilon_{ijm1}, \text{ if } j \text{ is an HMO} \]

where \( \tilde{h} = \frac{h_1}{h_1 + h_2} \), \( \tilde{\beta} = \frac{\beta h_2}{h_1 + h_2} \), and \( \tilde{\sigma}_v = \frac{\sigma_v h_2}{h_1 + h_2} \).

Note that (7) differs from a standard fixed effects logit model only by the inclusion of one parameter, \( \tilde{h} \).

The prior mean fixed effect parameters \( \bar{q} \) in (7) will be identified based on the popularity of plans. Since we include a fixed effect for the prior mean quality of each plan in each market, the price coefficient is identified by the extent to which changes in plan market share are related to changes in prices.

Importantly, we treat prices as exogenous. The assumption of exogenous prices reflects the institutional details in conjunction with the short time window surrounding the experiment that we analyze. The prices we observe are based on out-of-pocket costs charged to employees. We do not observe premiums charged to GM, which one would expect to be endogenous in a market setting, varying positively with quality. In contrast, out-of-pocket prices were set by GM. In our estimation, we will control for plan fixed effects. Thus, any endogeneity in these prices must arise from GM changing the out-of-pocket prices in response to changes in some unobserved attribute of the plan from 1996 to 1997. Conversations with GM suggest that this is a very unlikely source of price variation. Instead, changes in prices between 1996 and 1997 were
largely chosen to be correlated with the observed quality measures, in order to steer employees to high quality plans.

The relative magnitude of the ratings coefficients is identified based on whether there are systematic differences between 1996 and 1997 in the changes in HMO enrollment across markets, based on the ratings of plans in those markets. The geographic variation that arises because employees are located in many distinct markets means that we observe many ‘mini-experiments’. This diminishes the influence of unobservable plan traits that would more strongly influence the results if we observed only one market with a limited number of plans.

The absolute scale of the ratings coefficients is identified based on the net number of people switching to HMOs from non-HMO plans between 1996 and 1997. This identification, which is potentially problematic if there is a general trend towards HMO enrollment, is discussed further below.

We treat the ratings as exogenous, for two reasons. First, the new information was provided only to GM workers who are generally a small fraction of health plan employees. Second, the information, which was released in 1997, is based on 1995 plan performance, when most plans would not have anticipated the construction and release of the report card.

The learning parameter \( h \) will be identified based on how strongly the period 0 priors enter into the period 1 choices, and how these vary based on the difference between the priors and ratings. The standard deviation parameter \( \sigma \) will be identified based on whether period 1 exhibits a strong added variance in the choice probabilities for HMOs.

In the nested logit model, there is one additional parameter, the correlation parameter, \( \lambda \). This parameter will be identified from the fact that different markets have different choice sets.

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3 Sensitivity analysis suggests that the correlation between out-of-pocket prices and ratings does not substantively...
with different numbers of HMOs and PPOs. Thus, if two markets differ only in the number of HMOs, a high $\lambda$ would be consistent with the market with more HMOs having a proportionally higher share for HMOs while a low $\lambda$ would be consistent with the total market share of HMOs increasing by a lesser amount.

**Sensitivity and robustness**

Although the model is well-identified as specified, there are some potentially confounding explanations in the data. Foremost among these is the possibility that changes besides the ratings explain the difference in GM HMO enrollment between 1996 and 1997. In particular, aggregate U.S. HMO enrollment was increasing at a rapid rate over our study period, probably in part because of initiatives at other employers and greater familiarity with and acceptance of HMOs. Although we control for initiatives at GM, we are concerned that increased familiarity and acceptance may have caused some of the observed 2.8 percentage point increase in GM HMO enrollment. If present, failing to account for the increased familiarity and acceptance would inflate the absolute scale of the ratings coefficients and of our estimated value of information.

To account for changes in familiarity and acceptance over time, we would ideally want to allow for time–plan type interactions in the utility model. To formalize, define these interactions as $\delta_{p(j),t}$, where $p(j)$ indexes the plan type (FFSB, FFSE, PPO and HMO). Without loss of generality, we normalize the $\delta$’s for period 0 and for FFSE to be 0, which leaves us with 3 remaining parameters, $\delta_{\text{HMO},1}$, $\delta_{\text{PPO},1}$ and $\delta_{\text{FFSB},1}$.

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affect the conclusions (Scanlon et al., 2001).

4 InterStudy (1996, 1997) reports that the number of pure HMO enrollees in the U.S. increased from 52.5 million to 58.8 million people during 1996.
We can then add these terms to (7) for period 1, so that our model changes to:

\[
\begin{align*}
  u_{ijm1, j} &= \bar{q}_{jm} - \alpha P_{jm1} + \delta_{p(j),1} + \epsilon_{ijm1}, \text{ if } j \text{ is not an HMO} \\
  u_{ijm1} &= \tilde{h}_{ijm} + \tilde{p}_{ijm} + \tilde{\sigma}_i, \text{ if } j \text{ is an HMO.}
\end{align*}
\]

(8)

The \( \delta_{\text{ppo},1} \) and \( \delta_{\text{ffsb},1} \) terms in (8) can be identified from our data, and hence we include them in our estimation. However, since every employee received ratings in 1997, \( \delta_{\text{hmo},1} \) is perfectly collinear with the absolute scale of the ratings, and hence cannot be included as a separate parameter.

We thus examine three different normalizations for \( \delta_{\text{hmo},1} \). In our base results (Normalization 1), we set \( \delta_{\text{hmo},1} = 0 \), and ignore any trend towards HMOs. For Normalization 2, we use the enrollment patterns for salaried employees at a similar Midwest-based Fortune 50 manufacturing company that did not distribute ratings as a control group. That firm experienced an increase in HMO enrollment of 1.99 percentage points (from 40.78% to 42.77%) among its salaried employees between 1996 and 1997. Thus, for Normalization 2, we select \( \delta_{\text{hmo},1} \) to be the value that would have caused a 1.99 percentage point increase in GM HMO enrollment between 1996 and 1997 in the absence of ratings or any price or sample change.

Normalization 3 uses unionized employees at GM as a control group, since these employees were not provided with health plan report cards. The advantage of this normalization, relative to Normalization 2, is that the union workers had the same plan options as the salaried workers. However, during our study period new unionized employees at GM (of which there were relatively few) were required to join an HMO for their first two years of employment. Moreover, union workers may have different preferences than salaried workers and there may have been some spillover of information from salaried to union workers. HMO enrollment among GM unionized employees increased by 2.8 percentage points between 1996 and 1997
(from 28.0% to 30.8%). We believe these three normalizations span realistic values for trends to HMOs.

Given the importance of time–plan type interactions in explaining the absolute magnitude of the coefficients, one might expect that plan type dummies might also play a role. However, this is not the case. We can show theoretically that plan type dummies are perfectly collinear with the prior quality means and ratings, and that alternate values of plan type dummies do not affect our substantive conclusions on willingness to pay or switching behavior.

Moreover, while the normalization of $\delta_{\text{HMO},i}$ will affect the estimated switching behavior and the value of information, it will not affect the relative magnitude of the ratings coefficients. Thus, for instance, if we estimate that the increase in expected utility from having a plan be given rating B instead of rating A is worth $100, this figure will not change with the different normalizations. The fundamental reason for this is that our data allows the specification to identify, without normalization, how much individuals are willing to pay for a plan with a given set of ratings, relative to other ratings.

Another concern is that there could have been movements between HMOs, and not just to HMOs, in the absence of ratings. One possibility is that individuals may have systematically shifted towards highly rated plans even in the absence of ratings. This issue can be addressed by examining whether GM union employees, who did not receive ratings, shifted towards highly rated plans. Scanlon et al. (2002) found that using coarser measures of GM union workers’ enrollment at the plan level as a control group yielded virtually no difference in the results. Another possibility is that there could have been random movements between HMOs. Because we observe a large sample of markets cross–sectionally, we can control for this explanation with
plan–market–time random effects. We experimented with random effects but found that the random effects yielded virtually no change in the results. Hence, we do not report these figures.

Lastly, one may postulate that the effects of report cards vary within sub-populations of employees. For example, less healthy individuals may be more sensitive to information because they may care more or less sensitive because they are better informed in the absence of information. Preliminary analysis using age and number of dependents to proxy for health status did not indicate any substantive distinctions along these dimensions. Similarly, newly hired employees may be more sensitive to ratings information because their priors on plan qualities may have greater variance. Estimates from a model with only new hires are qualitatively very similar to our base results, although some coefficients are not statistically significant because of the smaller sample size. Hence, we also do not include results from these specifications.

**Estimation**

We estimate the parameters of the base specification of (7) using a simulated maximum likelihood estimation procedure. 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.

To define the likelihood, let $y_{int}$ denote the chosen plan for individual $i$ in market $m$ at time $t$. Additionally, for ease of notation, group all the parameters in $\theta$, so that $\theta = \left( \alpha, \hat{h}, \hat{\beta}, \bar{\sigma}, \lambda, \delta_{PPO1}, \delta_{FFSB1} \right)$, and all the exogenous variables in $x$ so that $x$ includes the

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5 Since the ratings were constructed from 1995 data, such shifts would have to come from learning about plans from 1996 experience and not from plan responses to ratings.
6 Note that $\lambda$ is a parameter only for the nested logit model.
ratings, prices, and identities of all offered plans in each market. Then, the log likelihood for an individual $i$ satisfies:

$$
\ln L(\theta | y, x) = \sum_{i,m,t} \ln \left( \frac{1}{NS} \sum_{s} \Pr(\text{Choice for enrollee } i,m,t \text{ is } y_{imt} | x, \theta, \nu_{ijms}) \right),
$$

where $NS$ is the number of simulation draws per individual (set to 20 for our results), $\nu_{ijms}$ is one simulation draw, and the probability of the observed choices are calculated using the logit or nested logit models as appropriate.\(^7\) See Berry (1994) for a derivation of these choice probabilities.

**IV. Data**

Our analysis is based on the health plan choices of employees at GM for two open enrollment periods, 1996 and 1997. The firm determined the set of health insurance plans from which employees could choose as well as the prices employees were charged for each plan. All employees had the FFSE and FFSB option, while HMO and PPO options depend on the employees’ zipcode of residence. The employees paid for the 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, which implies that the marginal contribution for health coverage came from out-of-pocket expenses.\(^8\)

During the 1997 open enrollment period, which occurred in the fall of 1996, GM provided health plan performance ratings for all available HMOs to non-union employees for the first time as part of the open enrollment materials. The performance ratings were based on

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\(^7\) The conclusions were insensitive to estimates made with fewer draws.
aggregated data from the Health Plan Employer Data and Information Set (HEDIS) and site visits to the HMOs [Scanlon et al. (2002)]. Because HEDIS data were only available for HMOs, no performance ratings were released for traditional fee-for-service (FFS) or preferred provider organization (PPO) plans. The release of the ‘report card’ provides the fundamental natural experiment that is the foundation of the analyses reported in this paper.

**Variable construction**

The key variables in this analysis are the ratings variables and the price charged to GM workers. HMOs were rated ‘below expected performance,’ ‘average performance,’ or ‘superior performance’ along six domains, labeled by GM as ‘preventive health care services’, ‘medical and surgical care’, ‘women’s health issues’, ‘access to care’, ‘patient satisfaction’, and ‘operational performance’. The underlying data typically relate to rates of utilization of selected services, survey responses regarding satisfaction, and various aspects of the provider group and measures of access. Outcome measures were generally not included in these early report cards and casemix adjustments were crude at best. Details regarding the variables and construction of the report card ratings are reported in Scanlon et al. (2002).

During the open enrollment period for 1997 enrollment, non-union GM employees were given an information sheet for each of the HMOs from which they could choose. The information sheet designated each plan as 1, 2, or 3 diamonds for each domain to represent the plan ratings. An example is provided in Figure 1, though no employee received the exact sheet represented in Figure 1 because no employees were offered the exact set of plans displayed.

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8 In both years the amount of flex dollars provided by GM was equivalent to the price for FFSB in each coverage category.
In some cases for HMOs in 1997, plans were given a rating of ‘missing’ for some domains because of insufficient data from the plans. Employees were informed that these plans did not provide sufficient information. We treat a ‘missing’ rating differently from no rating; note that all plans in 1996 and all non-HMO plans in 1997 have no rating. The reason is that a missing rating conveys information while no rating does not convey information. Hence, consumers may update their posterior quality based on a missing rating, but not if there is no rating.

Although there are six domains of performance, they are correlated and earlier work suggested we could not identify independent effects of ratings by domain of performance. Thus for each plan we create summary measures of quality based on the number of ratings that are Superior, Average, Below Average, or Missing (see Table 1). Apart from being an econometric convenience, such aggregation might be useful because individuals may not be able to process information from all the domains. They may adopt simplifying decision rules such as selecting plans with the most superior ratings or fewest below average ratings (Hibbard et al., 1997). Existing work from laboratory settings is consistent with such decision rules (Hibbard et al., 2000). In addition to these variables, we also include a dummy variable that indicates whether a plan was accredited.

We define price as the difference between the annual out-of-pocket price and the allotted flex dollars. Since the price coefficients in our models are identified by changes in plan out-of-pocket premiums over time, we reported this statistic (Table 1). One can see that the mean out-of-pocket prices for plans stayed relatively constant from 1996 to 1997, although there is

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9 The flex dollar amount varies from $1764 for employee coverage to $4812 for employee and family coverage. It does not change between 1996 and 1997.
substantial variation in prices over time for the same plan, reflected in a standard deviation of $436 on the change in price for family coverage.

Sample

The firm covered over 1.6 million active employees, retirees, and dependents. The analysis is based on the health plan choices over two years of the approximately 70,000 active, salaried employees based in the U.S. (Table 2). The set of health plans offered was very stable during the study period. We dropped from the analysis the 175 employees who were enrolled in one of five plans (three HMOs and two PPOs) that were offered in only one of the two years.

Employees could choose from four different coverage categories: single, employee and spouse, employee and children, and employee and family. The most popular coverage category is employee and family, while employee and spouse is second (Table 2). Coverage category could affect plan preferences in a variety of ways. For example, employees with children may be more interested in the set of available pediatricians and plan performance in the area of pediatric care.

In addition to the coverage category, employees could choose from a menu of different plans that depended on their zip code of residence. For our analysis, employees are assigned to geographic areas based on the set of HMO and PPO health plans from which they could choose. All employees who share a common set of plan choices are grouped into the same geographic area.

Geographic areas are mutually exclusive, but plans may serve multiple geographic areas. For example, plan A could be offered in San Francisco and south to Santa Cruz, and plan B

---

10 Dependents were not analyzed separately because they almost always made the same choice as the employee with GM coverage eligibility. Retirees were excluded because they are frequently Medicare-eligible, making the nature of plan choice different than for the non-Medicare population. Individuals with missing or obviously incorrect zip
could be offered in San Francisco and north through Marin County. This would result in three areas. Area 1 would represent Santa Cruz, with only plan A offered. Area 2 would represent Marin County, with only plan B offered. Area 3 would be San Francisco, with both plans offered.

For our analysis we define a ‘market’ as a particular geographic area/coverage category combination. We exclude plans that had zero enrollments in a market for either year. In most cases, this would occur when the plan was not a realistic choice for the employees in that market, largely due to geographic location. After excluding markets with fewer than 5 employees or only 1 plan, we have observations on 132 plans, including 106 HMOs, 24 PPOs and 2 FFS plans, spread across 525 geographic area/coverage markets. Table 3 documents descriptive statistics by markets. On average, markets have 3.83 plans (minimum = 2, maximum = 9). In 1996, the mean number of employees per cell was 133 (minimum = 5, maximum = 8246). In 1997, the cells were slightly smaller (mean = 130, minimum = 5, maximum = 7996).

V. Results

In this section, we detail the estimates of the model developed in Section 3. We then use the model, together with the estimated coefficients, to examine the impact of ratings on consumer behavior and valuations of information in the context of our Bayesian learning model.

Coefficient estimates

In Table 4, we provide the simulated maximum likelihood estimates of the model specified in (7) with the base normalization of \( \delta_{hmo_1} = 0 \). We provide the results from logit and code information also were omitted from the analysis. Union employees were not included because they were not
nested logit specifications. The logit is equivalent to the nested logit model where the parameter \( \lambda \) (from (2)) is constrained to be 1, so that there is no correlation between the unobservables for plans within a group. In addition, we also estimate a nested logit fixed effects model as a further check on the robustness of our parameter estimates. This fixed effects model is our base model with the constraint that \( \tilde{h} = 1 \) (i.e. no discounting of the prior).

The results are qualitatively similar between the different specifications. The coefficients on the fixed effects model are particularly similar to the nested logit learning model. For instance, the “superior quality” and “average quality” coefficients are virtually identical, and the price coefficient varies only between –0.257 and –0.264.

In all models, we find that the coefficient on price is significantly negative. For the specifications which allow learning, the prior weight \( \tilde{h} \) is much closer to 1 than to 0, but is significantly different from both. All four ratings on quality are significantly different from 0. While “below average quality” and “missing data” are negative, “average quality” and “superior quality” are positive. There is no statistical difference between the effects of average and superior ratings. The coefficient on “accredited” is negative, but only statistically significant in the logit model. In all models, the time interaction for FFSB, \( \delta_{FFSB,1} \), is negative and statistically significant, while the corresponding PPO interaction, \( \delta_{PPO,1} \), is insignificant and very close to 0.

In the nested logit model, the correlation parameter \( \lambda \) is estimated to be 0.561, and is significantly different from both 0 and 1. This suggests that we can reject the logit model because there are idiosyncratic preferences within plan types. Because of this result, we emphasize the nested logit results in the discussion that follows.

given the report card data and we lacked detailed data about enrollment for union members.
The models are estimated with 1488 prior mean quality parameters. Instead of listing each parameter value, the mean and standard deviation of the estimated coefficients within each group are summarized at the bottom of Table 4. We find that the magnitudes of the prior quality coefficients are much larger than the magnitudes of the ratings coefficients, which, in combination with the fact that $\hat{h}$ is close to 1, suggests that the prior information is much more important than the signal. Also, HMOs are estimated to have a negative prior quality level (i.e. lower than the FFSE plan), with the 818 prior mean HMO dummies having a mean of $-0.238$. This implies that for the majority of plans, average and superior ratings raise expectations about quality relative to the prior.\footnote{This result is sensitive to assumptions about whether there are plan–type fixed effects apart from quality. Our model assumes that there are not. Yet, plan–type fixed effects might exist, reflecting different benefits and restrictions on care. As discussed in Section 3, the presence of unaccounted plan–type fixed effects would not affect any other conclusion of the model.}

Table 5 reports coefficient estimates from the three nested logit normalizations discussed in Section 3, which differ in their values for the HMO time trend $\delta_{\text{HMO,1}}$. Normalization 1 (the base normalization, also in Table 4) sets $\delta_{\text{HMO,1}} = 0$, while Normalization 2 sets $\delta_{\text{HMO,1}} = 0.101$, chosen to yield a 1.99 percentage point increase in HMO enrollment with the base coefficients in the absence of price changes or ratings information. Normalization 3 sets $\delta_{\text{HMO,1}} = 0.143$, analogously chosen to yield a 2.8 percentage point increase in HMO enrollment. The collinear relationship between the normalizations implies a specific relationship between the coefficients. In particular, only the ratings coefficients change, and each of the four ratings coefficients change by the same amount.
Impact of ratings on choice

Table 6 shows the predicted effect of ratings on 1997 plan choices, using the estimates from the nested logit models under the three normalizations given in Table 5. To find these figures, we compute individuals’ choices in the absence and presence of ratings information. We perform the computation by simulating over the unobservables $e_{ijmt}$ and $v_{ijm}$ for each individual in 1997. When simulating the counterfactual absence of ratings, we assume that the individuals do not update at all and hence that their posterior expectation of quality is identical to their prior expectation. We also assume that the unobservables $e_{ijmt}$ and $v_{ijm}$ do not change with the implementation of ratings.

The first row reports the predicted net changes in market share between 1996 and 1997 assuming no ratings had been released. These are the baseline estimates of what would have happened in the absence of ratings. The 0.21 percentage point increase in HMO market share that is reported for Normalization 1 is due to changes in prices and the set of employees. The comparable increase for Normalization 2 is 2.15 percentage points and for Normalization 3 it is 2.96 percentage points. These figures, which are larger because they incorporate the time trend $\delta_{HMO,1}$, approximate what happened in the comparable firm or among GM union workers.

Rows 2 through 4 estimate the impact of ratings under several scenarios. In row 2 we assume all plans had average scores on all ratings. Under this scenario, all three normalizations report a 6.86 percentage point increase in HMO market share, which is the highest possible HMO enrollment increase across ratings. Row three assumes all of the plans had one “below average” rating and the rest were average, yielding a slightly lower figure. The fourth row estimates the impact given the actual ratings that were released, indicating that all models predict
a 2.81 percentage point increase in share from 1996 to 1997. Note that these values are invariant to the normalization used.

In contrast, Normalizations 2 and 3 predict that a smaller part of the observed increase in HMO market share is attributable to ratings. For instance, under Normalization 1, the release of the actual ratings caused a 2.60 percentage point increase in HMO share, while Normalization 2 reports this figure as a much smaller 0.66 percentage points. These figures are all relatively modest compared to the 36.7 percent of employees who chose HMOs in 1996.

**Willingness to pay to avoid plans with below average ratings**

Given our estimates in Table 4, it is straightforward to compute the willingness of individuals to pay for plans with better ratings. This computation can be done by dividing the utility gain by the marginal utility of money, which is \( \alpha \), the coefficient on price. Using the nested logit model, the estimates suggest that posterior expected utility increases a significant amount from avoiding “below average quality” or “missing data” ratings: For instance, the increase in posterior utility from a plan if one out of six quality characteristics changes from “below average” to “average” is worth 

\[
1000 \times (0.052 - (-0.021)) / 0.264 \approx 276/\text{year}.
\]

Essentially employees would pay $276/year to avoid a plan with one extra below average rating. This figure does not change across the different normalizations given in Table 5, but is mildly affected by specification. The estimates for the fixed effects model and the (non-nested) logit model are very similar, $259 and $275, respectively.
Value of ratings

A direct measure of the ex–post utility gain from the access to ratings is the difference between the posterior utility of the plan chosen in the presence of ratings and the posterior utility of the plan that would have been chosen in the absence of ratings. To formalize, define expected utility for a given consumer \( U_{imi} (\mathcal{Z}, j) \) to be a function of the information \( \mathcal{Z} \) and the choice \( j \) and let \( Y_{imi} (\mathcal{Z}) \) be the utility maximizing choice given information \( \mathcal{Z} \). We can summarize the realized 1997 information as the signals for all plans in the market, \( \mathcal{Z} = s_{*m} \), and the 1996 information as the null set, \( \mathcal{Z} = \emptyset \). Thus, going back to (1) and (9) in the model section, we can write \( U_{imi} (s_{*m}, j) = u_{ijm1} \), and \( Y_{imi} (s_{*m}) = y_{im1} \).

Given these definitions, we can formalize the utility gain defined above as:

\[
U = \sum_{m} \sum_{i} \left[ U_{imi} (s_{*m}, Y_{imi} (s_{*m})) - U_{imi} (s_{*m}, Y_{imi} (\emptyset)) \right].
\]

By dividing \( U \) by the coefficient on price, we can express the value gain in dollars.

While (10) is an ex–post measure of value for an individual, it is equivalent to the population ex–ante value of information, if we are willing to assume that the ex–post distribution of ratings was equal to the ex–ante distribution. Specifically, the standard definition of the ex–ante value of information is given by DeGroot (1970, p. 197), who considers the case of observing signals with subsequent decisions. Defining \( f(s,q) \) to be the ex–ante density of signals and quality, the DeGroot measure is:

\[
V = \sum_{m} \sum_{i} \int \left[ U_{imi} (s, Y_{imi} (s)) - U_{imi} (s, Y_{imi} (\emptyset)) \right] f(q | s) f(s) ds dq
\]

\[
= \sum_{m} \sum_{i} \left[ U_{imi} (s, Y_{imi} (s)) - U_{imi} (s, Y_{imi} (\emptyset)) \right] f(s) ds.
\]
where the equality follows from the fact that the expected utility and decision depend only on the signal. Given the assumption on the equality of ex–ante and ex–post signal distributions, (10) will converge to (11) for a large set of consumers, and our value measure will approximate the ex–ante measure.

Table 7 presents results on the value of the ratings $U/\alpha$ and the percent of employees who switched plans as a result of the ratings, using the three normalizations from Table 5. We find that, under Normalization 1, the information was worth an average of $27 per employee (or $1.86 Million total) per year, and approximately $22 under Normalizations 2 and 3. The fraction of enrollees who switch plans as a result of the ratings varies from 4.49 to 5.25 percent across the normalizations. In contrast to the differences across normalizations in the change in HMO share due to the ratings (from Table 6), these results are very similar across the normalizations. The reason for this is that most of the switching behavior, and hence most of the value of information, is caused by people switching away from HMOs with low signals and towards HMOs with high signals and not by any aggregate movement from FFS plans towards HMOs.

The estimates of the value of information are derived directly from our model and are based on revealed preferences. They do not reflect several potentially important issues related to the value of information. For example, the rating construction process has been widely, and probably justifiably, criticized. If consumer responses reflect a misperception about what the ratings measure, as opposed to a rational response to new data, the value of information estimates would not reflect the true value. Similarly, our definition of value assumes that

---

12 These estimated values of information are small relative to the $276 willingness to pay to change just one out of six ratings from below average to average. The reason for this disparity is that the quality priors are much larger than the price or ratings coefficients, and hence only a small fraction of the employees switched plans as a result of the ratings. Thus, even though the above signal change is worth $276, most people would not switch plans just because of a $276 change in utility. For the 95% of enrollees who did not switch plans as a result of the ratings, the ratings had no ex–post value.
information only provides value through the ability to change enrollment patterns. A consumer who does not switch plans gains no utility from learning that her plan is superior and loses no utility from learning that her plan is below average, though one could certainly argue that such effects should be considered in the calculations.

Though our measures of value are incomplete, the question arises as to whether they are large or small. The estimated value of information is a small fraction of the cost of health plans. One could also compare the estimates to the costs of generating the information. Such estimates are difficult to obtain. Wholey et al. (2000) report that the cost for each plan to produce information is $2.67 per enrollee, which is much smaller than our estimates of value. However, this does not include the costs to GM of creating and disseminating the report card or the cost to health care providers of collecting the information.

### Relationship between prior and signal

Figure 2 details the relationship between the prior mean on quality and the mean quality signal, for all HMOs. The figure plots the prior and signal for each of the 818 HMO observations, as well as a fitted regression line. The mean quality signal is evaluated by setting $v_{ijm} = 0$. These results are invariant across the normalizations in Table 5.

One can see from the figure that there is a distinct, though weak, positive relationship between the prior mean and the mean signal. In particular, we find a 0.14 correlation that is statistically significant. This suggests that, on average, the ratings reinforced prior knowledge. Moreover, one can also see that the variance of the mean signals from the ratings is much smaller than the variance of the prior mean coefficients.
VI. Conclusions

Economists have long recognized the importance of information in markets. They also realize that mechanisms exist to inform consumers even when there is a lack of formally provided information on product attributes. In spite of this, relatively little literature has examined changes in information structure and their impact on behavior. The health care industry presents an ideal opportunity to address these issues because of the salience of information in this market and the continuing evolution of efforts to provide explicit information on health plan quality.

This paper assesses the impact of the release of information on health plan choices by estimating a Bayesian learning model on a natural experiment data set. We find that information does have an effect on health plan choice. Consumers have a moderately large willingness to pay to avoid plans with bad ratings. However, relatively few people switch plans as a result of the ratings, implying a lower, but still positive, per-capita value of information.

Thus the results suggest that despite the existence of informal information generating mechanisms, such as social learning and reputation, formal ratings information is still valuable. Moreover, these results are also consistent with the premise that information barriers deter enrollment in managed care and that removing of those barriers through explicit provision of information may encourage managed care enrollment.
References


### 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.

<table>
<thead>
<tr>
<th>Plan Code</th>
<th>Plan Description</th>
<th>NCCN Accredited?</th>
<th>Benchmark HMO?</th>
<th>Oper-</th>
<th>Preventive Care</th>
<th>Medical/Surgical Care</th>
<th>Women's Health</th>
<th>Access to Care</th>
<th>Patient Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>0001</td>
<td>Basic Medical Plan</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0002</td>
<td>Enhanced Medical Plan</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPO 2190</td>
<td>Blue Preferred Plus</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HMO 2101</td>
<td>Care Choices HMO</td>
<td>Yes</td>
<td>No</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>HMO 2108</td>
<td>BCN G Lakes SW MI</td>
<td>Yes</td>
<td>No</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>HMO 2113</td>
<td>BCN Health Central</td>
<td>Yes</td>
<td>No</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>HMO 2116</td>
<td>Priority Health</td>
<td>Yes</td>
<td>No</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>HMO 2117</td>
<td>Care Choices HMO W MI</td>
<td>Yes</td>
<td>No</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>HMO 2118</td>
<td>BCN West Michigan</td>
<td>Yes</td>
<td>No</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

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

Michigan - Lansing and West
### Table 1

#### Plan Characteristics

<table>
<thead>
<tr>
<th></th>
<th>All Plans: (HMO/PPO/FFS)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
</tr>
<tr>
<td>Annual Price* (1996) Employee Coverage</td>
<td>132</td>
<td>$477</td>
</tr>
<tr>
<td>Annual Price* (1997) Employee Coverage</td>
<td>132</td>
<td>$475</td>
</tr>
<tr>
<td>Annual Price* (1996) Family Coverage</td>
<td>132</td>
<td>$1317</td>
</tr>
<tr>
<td>Annual Price* (1997) Family Coverage</td>
<td>132</td>
<td>$1309</td>
</tr>
</tbody>
</table>

|                                | HMO Plans |                                                                 |
|                                | N    | Mean | Std. Dev. | Min | Max  |
| Sum Superior                   | 106  | 2.15 | 1.78      | 0   | 6    |
| Sum Average                    | 106  | 1.95 | 1.30      | 0   | 5    |
| Sum Below Average              | 106  | 1.41 | 1.30      | 0   | 5    |
| Sum Missing                    | 106  | 0.49 | 1.09      | 0   | 5    |
| Accreditation                  | 106  | Yes  | 75 (71%)  | No  | 31 (29%) |

*The annual prices reflect the difference between the GM ‘price-tag’ and the allotted flex dollars. These prices do not include the $504 employees receive if they decline GM sponsored coverage.
Table 2

Sample Distribution

<table>
<thead>
<tr>
<th>Year</th>
<th>HMO</th>
<th>PPO</th>
<th>FFS</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>25,560</td>
<td>10,906</td>
<td>33,371</td>
<td>69,837</td>
</tr>
<tr>
<td>1997</td>
<td>26,909</td>
<td>10,228</td>
<td>31,146</td>
<td>68,283</td>
</tr>
<tr>
<td>1997: Tier 1</td>
<td>5,699</td>
<td>2,426</td>
<td>8,533</td>
<td>16,658</td>
</tr>
<tr>
<td>(Employee)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997: Tier 2</td>
<td>6,001</td>
<td>2,928</td>
<td>8,247</td>
<td>17,176</td>
</tr>
<tr>
<td>(Emp/Spouse)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997: Tier 3</td>
<td>2,052</td>
<td>891</td>
<td>1,707</td>
<td>4,650</td>
</tr>
<tr>
<td>(Emp/Child)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997: Tier 4</td>
<td>13,157</td>
<td>3,983</td>
<td>12,659</td>
<td>29,799</td>
</tr>
<tr>
<td>(Family)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996 Plan Type for Employees who Switched Plans</td>
<td>1,837</td>
<td>832</td>
<td>2,632</td>
<td>5,301</td>
</tr>
<tr>
<td>1997 Plan Type for Employees who Switched Plans</td>
<td>2,642</td>
<td>713</td>
<td>1946</td>
<td>5,301</td>
</tr>
</tbody>
</table>

Universe: Active salaried employees kept in sample.
### Table 3

*Market Characteristics*

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of plans offered</td>
<td>525</td>
<td>3.83</td>
<td>1.45</td>
<td>2</td>
<td>9</td>
</tr>
<tr>
<td>Number of HMO plans offered</td>
<td>525</td>
<td>1.56</td>
<td>1.08</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Number of PPO plans offered</td>
<td>525</td>
<td>0.62</td>
<td>0.55</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Number of 1996 employees</td>
<td>525</td>
<td>133</td>
<td>509</td>
<td>5</td>
<td>8246</td>
</tr>
<tr>
<td>Number of 1997 employees</td>
<td>525</td>
<td>130</td>
<td>494</td>
<td>5</td>
<td>7996</td>
</tr>
</tbody>
</table>

Note: A market corresponds to a particular geographic area and coverage tier.
<table>
<thead>
<tr>
<th>Model:</th>
<th>Logit</th>
<th>Nested Logit</th>
<th>Fixed effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum Superior quality ((\hat{\beta}))</td>
<td>0.047 (8.617)</td>
<td>0.035 (7.916)</td>
<td>0.035 (7.935)</td>
</tr>
<tr>
<td>Sum Average quality ((\hat{\beta}))</td>
<td>0.064 (8.000)</td>
<td>0.052 (8.004)</td>
<td>0.052 (8.098)</td>
</tr>
<tr>
<td>Sum Below average quality ((\hat{\beta}))</td>
<td>-0.046 (-6.108)</td>
<td>-0.021 (-2.959)</td>
<td>-0.015 (-2.286)</td>
</tr>
<tr>
<td>Sum Missing data ((\hat{\beta}))</td>
<td>-0.100 (-8.015)</td>
<td>-0.061 (-4.898)</td>
<td>-0.054 (-4.411)</td>
</tr>
<tr>
<td>Accredited ((\hat{\beta}))</td>
<td>-0.072 (-2.231)</td>
<td>-0.032 (-1.249)</td>
<td>-0.026 (-1.046)</td>
</tr>
<tr>
<td>Price ((\alpha)) ($1000s)</td>
<td>0.398 (7.755)</td>
<td>0.264 (5.735)</td>
<td>0.257 (5.603)</td>
</tr>
<tr>
<td>Prior weight ((h))</td>
<td>0.958 (88.35)</td>
<td>0.954 (80.98)</td>
<td>1</td>
</tr>
<tr>
<td>Std. dev. of random component of rating ((\sigma_v))</td>
<td>0.140 (2.694)</td>
<td>0.126 (3.457)</td>
<td>0.174 (4.815)</td>
</tr>
<tr>
<td>Component of error term that is iid ((\lambda))</td>
<td>1</td>
<td>0.561 (7.509)</td>
<td>0.528 (7.110)</td>
</tr>
<tr>
<td>PPO–time interaction ((\delta_{PPO,1}))</td>
<td>0.006 (0.347)</td>
<td>0.007 (0.426)</td>
<td>0.005 (0.282)</td>
</tr>
<tr>
<td>FFSB–time interaction ((\delta_{FFSB,1}))</td>
<td>-0.077 (-3.313)</td>
<td>-0.043 (-3.022)</td>
<td>-0.040 (-2.950)</td>
</tr>
<tr>
<td>Mean / std. dev. prior quality ((\bar{q})) for HMOs (N=818)</td>
<td>-0.514 1.293</td>
<td>-0.238 1.050</td>
<td>-0.219 1.015</td>
</tr>
<tr>
<td>Mean / std. dev. prior quality ((\bar{q})) for PPOs (N=327)</td>
<td>-0.438 0.825</td>
<td>-0.562 0.796</td>
<td>-0.568 0.795</td>
</tr>
<tr>
<td>Mean / std. dev. prior quality ((\bar{q})) for FFSB (N=343)</td>
<td>-1.659 0.760</td>
<td>-0.948 0.429</td>
<td>-0.895 0.404</td>
</tr>
<tr>
<td></td>
<td>Normalization 1</td>
<td>Normalization 2</td>
<td>Normalization 3</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------</td>
<td>-----------------</td>
<td>-----------------</td>
</tr>
<tr>
<td></td>
<td>$\delta_{\text{HMO},1} = 0$</td>
<td>$\delta_{\text{HMO},1} = 0.101$</td>
<td>$\delta_{\text{HMO},1} = 0.143$</td>
</tr>
<tr>
<td>Sum Superior quality ($\tilde{\beta}$)</td>
<td>0.035 (7.916)</td>
<td>0.018 (3.308)</td>
<td>0.011 (2.490)</td>
</tr>
<tr>
<td>Sum Average quality ($\tilde{\beta}$)</td>
<td>0.052 (8.004)</td>
<td>0.035 (6.282)</td>
<td>0.028 (4.340)</td>
</tr>
<tr>
<td>Sum Below average quality ($\tilde{\beta}$)</td>
<td>-0.021 (-2.959)</td>
<td>-0.038 (-4.534)</td>
<td>-0.045 (-6.314)</td>
</tr>
<tr>
<td>Sum Missing data ($\tilde{\beta}$)</td>
<td>-0.061 (-4.898)</td>
<td>-0.078 (-5.653)</td>
<td>-0.085 (-6.802)</td>
</tr>
<tr>
<td>Accredited ($\tilde{\beta}$)</td>
<td>-0.032 (-1.249)</td>
<td>-0.032 (-1.249)</td>
<td>-0.032 (-1.249)</td>
</tr>
<tr>
<td>Price ($\alpha$) ($\text{1000s}$)</td>
<td>0.264 (5.735)</td>
<td>0.264 (5.735)</td>
<td>0.264 (5.735)</td>
</tr>
<tr>
<td>Prior weight ($\tilde{h}$)</td>
<td>0.954 (80.98)</td>
<td>0.954 (80.98)</td>
<td>0.954 (80.98)</td>
</tr>
<tr>
<td>Std. dev. of random component of rating ($\tilde{\sigma}$)</td>
<td>0.126 (3.457)</td>
<td>0.126 (3.457)</td>
<td>0.126 (3.457)</td>
</tr>
<tr>
<td>Component of error term that is iid ($\lambda$)</td>
<td>0.561 (7.509)</td>
<td>0.561 (7.509)</td>
<td>0.561 (7.509)</td>
</tr>
<tr>
<td>PPO–time interaction ($\delta_{\text{PPO,1}}$)</td>
<td>0.007 (0.426)</td>
<td>0.007 (0.426)</td>
<td>0.007 (0.426)</td>
</tr>
<tr>
<td>FFSB–time interaction ($\delta_{\text{FFSB,1}}$)</td>
<td>-0.043 (-3.022)</td>
<td>-0.043 (-3.022)</td>
<td>-0.043 (-3.022)</td>
</tr>
<tr>
<td>Mean / std. dev. prior quality ($\overline{q}$) for HMOs (N=818)</td>
<td>-0.238 1.050</td>
<td>-0.238 1.050</td>
<td>-0.238 1.050</td>
</tr>
<tr>
<td>Mean / std. dev. prior quality ($\overline{q}$) for PPOs (N=327)</td>
<td>-0.562 0.796</td>
<td>-0.562 0.796</td>
<td>-0.562 0.796</td>
</tr>
<tr>
<td>Mean / std. dev. prior quality ($\overline{q}$) for FFSB (N=343)</td>
<td>-0.948 0.429</td>
<td>-0.948 0.429</td>
<td>-0.948 0.429</td>
</tr>
</tbody>
</table>
### Table 6

**Effect of Ratings on Plan Choice**

<table>
<thead>
<tr>
<th></th>
<th>Norm 1</th>
<th>Norm 2</th>
<th>Norm 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Change in HMO market share if no ratings released</td>
<td>0.21%</td>
<td>2.15%</td>
<td>2.96%</td>
</tr>
<tr>
<td>(2) Change in HMO market share if all HMOs had average ratings</td>
<td>6.86%</td>
<td>6.86%</td>
<td>6.86%</td>
</tr>
<tr>
<td>(3) Change in HMO market share if all HMOs had 5 average ratings and 1 below average rating</td>
<td>5.39%</td>
<td>5.39%</td>
<td>5.39%</td>
</tr>
<tr>
<td>(4) Change in HMO market share given actual ratings</td>
<td>2.81%</td>
<td>2.81%</td>
<td>2.81%</td>
</tr>
<tr>
<td>Difference between (2) and (1)</td>
<td>6.65%</td>
<td>4.70%</td>
<td>3.90%</td>
</tr>
<tr>
<td>Difference between (3) and (1)</td>
<td>5.18%</td>
<td>3.24%</td>
<td>2.43%</td>
</tr>
<tr>
<td>Difference between (4) and (1)</td>
<td>2.60%</td>
<td>0.66%</td>
<td>–0.15%</td>
</tr>
</tbody>
</table>

Note: The table reports the change in the total share of GM employees choosing HMOs relative to the 1996 levels: All figures are computed using the estimated parameters of the model.
### Table 7

Value of Ratings

<table>
<thead>
<tr>
<th></th>
<th>Normalization 1</th>
<th>Normalization 2</th>
<th>Normalization 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean value for one year of coverage</td>
<td>$27</td>
<td>$22</td>
<td>$22</td>
</tr>
<tr>
<td>Percent of employees who switch plans as a result of the ratings</td>
<td>5.28%</td>
<td>4.55%</td>
<td>4.49%</td>
</tr>
</tbody>
</table>

Note: All figures are computed using the estimated parameters of the model.
Figure 2

Relationship between prior and signal, nested logit model

Note: The figure reports the prior mean quality and the mean signal for each HMO in each market, as well as a fitted linear regression trend line.