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ABSTRACT

Health plans paid by capitation have an incentive to distort the quality of services they offer to attract profitable and to deter unprofitable enrollees. We characterize plans' rationing as imposing a "shadow price" on access to various areas of care and show that the profit maximizing shadow price depends on the dispersion in health costs, how well individuals forecast their health costs, the correlation between use in different illness categories, and the risk adjustment system used for payment. We further show how these factors can be combined in an empirically implementable index that can be used to identify the services that will be most distorted in competition among managed care plans. A simple welfare measure is developed to quantify the distortion caused by selection incentives. We illustrate the application of our ideas with a Medicaid data set, and conduct policy analyses of risk adjustment and other options for dealing with adverse selection.

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I. Introduction

Many countries are turning to competition among managed care plans to make the tradeoff between cost and quality in health care. In the U.S., major public programs and many private health insurance plans offer enrollees a choice of managed care plans paid by capitation.[1] Recent estimates are that 40% of the poor and disabled in Medicaid and 14% of the elderly are enrolled in managed care plans paid by capitation (Medicare Payment Advisory Commission, 1998). Both figures are bound to increase rapidly. In private health insurance, about three-quarters of the covered population is in some form of managed care, though in many cases, employers continue to bear some or all of the health care cost risk (Jensen, 1997). Health policy in the Netherlands, England, and other countries shares similar essential features. Israel, for example, recently reformed its health care system so that residents may choose among several managed care plans which all must offer a comprehensive basket of health care services set by regulation. A common feature of such reforms is for plans to receive a risk-adjusted capitation payment from the government or private payers for each enrollee.

The capitation/managed care strategy relies on the idea that costs are controlled by the capitation payment and the "quality" of services is enforced by the market. The basic rationale for this health policy is the following: the capitation payment plans receive gives them an incentive to reduce cost (and quality), while the opportunity to attract enrollees gives plans an incentive to increase quality (and cost). Ideally, these countervailing incentives lead plans to make efficient choices about service quality.

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[1] For representative discussions in the U.S. context, see Cutler (1995), Newhouse (1994), Enthoven and Singer (1995). President Clinton's proposed health care reform would have forced the health insurance market in that direction. See also Netanyahu Commission (1990) for Israel, and van Vliet and van de Ven (1992) for the Netherlands. For a discussion of state-level reforms, see Holohan et al. (1995).

Competition in the health insurance market has well-known drawbacks, the most troubling one being adverse selection. As competition among managed care plans becomes the predominant form of market interaction in health care, adverse selection takes a new form which may actually be much harder to address in policy, relative to the case of conventional health insurance. With old-fashioned fee-for-service insurance arrangements, a health plan might provide good coverage for, say, child care, to attract young healthy families, and provide poor coverage for hospital care for mental illness. If it appeared that refusing to cover hospital care for mental illness was motivated by selection concerns, public policy could force private insurers to offer the coverage through mandated benefit legislation. As health insurance moves away from conventional fee-for-service plans, where enrollees have free choice of providers, and becomes "managed care," the mechanisms a health insurance plan uses to effectuate selection change from readily regulated coinsurance, deductibles, limits and exclusions, to more difficult-to-regulate internal management processes which ration care in a managed care plan.

Researchers on the economics of payment and managed care are well aware of the issue. Ellis (1998) labels underprovision of care to avoid bad risks as "skimping." Newhouse et al. (1997) call it "stinting." Cutler and Zeckhauser (1997) call it "plan manipulation." As Miller and Luft (1997:20) put it:

> "Under the simple capitation payments that now exist, providers and plans face strong disincentives to excel in care for the sickest and most expensive patients. Plans that develop a strong reputation for excellence in quality of care for the sickest will attract new high-cost enrollees…."

The flip side, of course, is that in response to selection incentives the plan might provide too much of the services used to treat the less seriously ill, in order to attract good risks. "Too much" is meant in an economic sense. A plan, motivated by selection, might provide so much of certain services that the enrollees may not benefit in accord with what it costs the plan to provide them (Newhouse et al., 1997:28). An important implication of this observation is capitation and managed care can be expected to generate too little care in some areas and too much care in others.[2] This leads, then, to the questions: How does a regulator know which services a managed care plan is skimping on/over-providing to affect risk selection? Even if the regulator did know, what could it do about it?

Motivated by these questions, public regulatory bodies and private payers have recently become very interested in monitoring the quality of care in managed care plans. Monitoring health care quality has become an industry, virtually overnight, though no single approach has gained wide acceptance. Monitoring consists of identification of measureable standards (consumer satisfaction, health outcomes, quality of inputs) against which a plan's performance is compared. There are many drawbacks to this approach, from a policy and an economic standpoint. At a recent conference, observers noted that standards have proliferated, and it is difficult to find standards that are sensitive to system characteristics (Mitchell et al., 1997). The standards are at best imperfect indicators of value to enrollees. Ranking the importance of different standards is largely arbitrary. Quality can be too high as well as too low, and existing approaches are all oriented to a minimum not a maximum standard. Gathering information on many standards for many plans in a timely fashion is very expensive. Plans do not all have

[2] Miller and Luft (1997) reviewed 37 studies meeting research standards of quality of care in managed care organizations paid by capitation. In comparison to care outside of capitation/managed care, quality was found to be sometimes higher and sometimes lower. However, the authors called attention to several studies showing systematically lower quality for Medicare enrollees with chronic conditions, reflecting a concern for chronic illnesses expressed by others, such as Schlesinger and Mechanic (1993). For example, recent data released by the National Committee on Quality Assurance (NCQA) reveals that on average, managed care plans use beta-blockers to treat heart attacks 61.9% of the time (Standard: 100%). The plans screen women for cervical cancer (70.9%) and do mammagraphies (70.4%) at higher rates (Standard: 100%). It is difficult to interpret such data in terms of incentives to supply care of various types (Health Care Compass, 1997).

adequate administrative capability (Gold, 1995). Enrollees move in and out of plans, making measures based on performance at the person level difficult to implement. Rewarding a subset of quality indicators may distort performance by health plans.

In this paper we take a very different approach to address the question of how to monitor selection-related quality distortions in the market for health insurance with managed care. We start from the assumption that plans maximize profit. We show that to do so, each plan rations by, in effect, setting a service-specific "shadow" price for each service. We interpret the shadow price as characterizing the *incentives* a plan has to distort services away from the efficient level. The shadow price captures how tightly or loosely a profit maximizing plan should ration services in a particular category in its own self-interest. Services that the plan should restrain will be characterized by higher shadow prices than services that the plan should provide generously. The shadow price is an operational concept, measurable with data from a health plan. We take the ratio of the shadow price for a particular service in relation to some numeraire service to create a "distortion index."

After developing the shadow price measure of selection distortions and discussing the properties of services that will be over and underprovided (Section II), we illustrate how these shadow prices can be calculated with data from a health plan (Section III). Our purpose at this stage is not to draw conclusions about which services are distorted. To do so one needs data, just now emerging, on the behavior of managed care plans. Our purpose here is to illustrate how to calculate the shadow prices with health plan data, and to confront the issues involved in an empirical application. We go on to illustrate how our measures can be used to evaluate the efficiency properties of various strategies to deal with adverse selection, such as risk adjusting payments to managed care plans, and segmenting insurance markets with "carve outs."

An analogy might be helpful at this point. Another question about the efficiency of markets is more familiar: Which firms' outputs are most distorted by monopoly power? The direct approach to answering this would be to compare the existing price of each firm to an estimate of what the price would be in a competitive market. But since hypothesized competitive prices cannot be easily observed, the more common, indirect approach is to examine each firm's elasticity of demand. Following Lerner (1934), we could use firms' elasticities to rank firms according to where output is likely to be distorted most. Demand elasticity does not *directly* measure the distortion, it simply is a measure of how bad the distortion would be, assuming the firm acts so as to maximize profit. In the market for managed care, the condition for profit maximization involves more than an elasticity-driven markup, but the method we use for exposing distortions is analogous to Lerner's for flagging monopoly. We do not measure the distortion directly, but we do measure the strength of the economic forces creating the distortion.

Our analysis is based on a model of a profit maximizing managed care plan competing for enrollees. We assume that the plan cannot select enrollees on the basis of their future health care costs, either because the plan does not have this information or because there is an "open enrollment" requirement. Consumers, however, have some information about their future health care costs. The plan sets the quality of services in light of its beliefs about consumers' knowledge. We analyze the incentives of the plan to distort quality in order to attract "good" enrollees - those with low expected future health care costs in relation to the capitated payment plans are paid. We find that incentives to a plan to devote resources to services depend on the demand for that service among the plan's current enrollees, how well potential enrollees can forecast their demand for the service, whether the distribution of those forecasts is uniform or skewed in the population, the correlation of those forecasts with forecasts of other health care use, and on the risk-adjustment system used to pay for enrollees. We show how all these factors fit together into an index for each service the plan provides.

Many papers have shown that consumers choose health plans on the basis of their anticipated spending. Medicare's program for paying HMOs by capitation has been studied repeatedly in this regard. In a representative analysis, Hill and Brown (1990) find that individuals choosing to join HMOs for the first time were spending 23% less than those who do not choose to join and had a lower mortality rate in the period after joining. (See also Eggers and Prihoda, 1982; Garfinkel et al., 1986; Brown, Bergeron and Clement, 1993). The finding of significant adverse selection in Medicare continues to be borne out by more recent studies (Medicare Payment Advisory Commission, 1998). Numerous other studies have also found among other populations that those choosing to join HMOs are "healthier" in some ways than those not joining (Cutler and Reber, 1997; Cutler and Zeckhauser, 1997; Glied et al., 1997; Robinson, Gardner and Luft, 1993; Luft and Miller, 1988.

Risk-adjustment of payments to managed care plans are intended to counteract incentives to distort services. If plans are paid more for enrollees likely to be costly, the plan will not shun these enrollees. Individuals choose plans on the basis of what they (the individuals) can predict. A risk adjustment system that picks up the predictable part of the variance in health costs is thus able to address dangers of selection. How much of the health care cost variance individuals can anticipate is not known. To get some idea, empirical researchers have assumed that individuals know the information contained in certain potential explanatory variables, and then investigated how much of the variance is explained by these covariates. In the most well-known of these studies, Newhouse et al. (1989) assume that individuals know the information contained in their individual time invariant contribution to the variance – in other words, they can predict the 24 percent of the variance picked up by the person fixed effects in a multiyear regression. They regarded this as a reasonable "minimum" of what individuals could predict. Currently available risk adjusters miss a good deal of this predictable variance. Medicare's current risk adjusters explain about 2 percent of total variance; proposed refinements improve the explanatory power considerably, but only to about 9 percent (Ellis et al., forthcoming; Weiner et al., 1996). There remains considerable room for systematic selection that would not be captured by a payment system based on existing risk adjusters.

II. Profit Maximization in Managed Care

We describe the behavior of a health plan (such as an HMO) in a market for health insurance in which potential enrollees make a choice about their health plan. The health plan is paid a premium (possibly risk-adjusted) for each individual that joins. Individuals differ in their need/demand for health care, and choose a plan to maximize their expected utility. "Health care" is not a single commodity but a set of services -- maternity, mental health, emergency care, cardiac care, and so on. A health plan chooses a rationing or allocation rule for each service. The plan's choice of rules will affect which individuals find the plan attractive and will therefore determine the plan's revenue and costs. We assume that the plan must accept every applicant, and we are interested in characterizing the plan's incentives to ration services.

Utility and Plan Choice

A health plan offers S services. Let m_{is} denote the amount the plan will spend on providing service s to individual i, if he joins the plan, and let: $m_i = \{m_{i1}, m_{i2}, ..., m_{iS}\}$. The dollar value of the benefits individual i gets from a plan, $u_i(m_i)$, is composed of two parts, a valuation of the services an individual gets from the plan, and a component of valuation that is independent of services. Thus,

$$u_i(m_i) = v_i(m_i) + \mu_i \quad (1)$$

where,

$$v_i(m_i) = \sum_s v_{is}(m_{is}).$$

v_i is the service-related part of the valuation and is itself composed of the sum of the individual's valuations of all services offered by the plan. $v_{is}(\bullet)$ is the individual's valuation of spending on service s, also measured in dollars, where $v'_{is} > 0$, $v''_{is} < 0$.[3] For now we proceed by assuming that the individual knows $v_i(m_i)$ with certainty. Later, we consider the case when the individual is uncertain about his $v_i(m_i)$. The non-service component is μ_i, an individual-specific factor (e.g. distance or convenience) affecting individual i's valuation, known to person i. From the point of view of the plan, μ_i is unknown, but is drawn from a distribution $\Phi_i(\mu_i)$. We assume that the premium the plan receives has been predetermined and is not part of the strategy the plan uses to influence selection. Premium differences among plans (if premiums are paid by the enrollees) can be regarded to be part of μ_i.

The plan will be chosen by individual i if $u_i > \bar{u}_i$, where $\bar{u}_i$ is the valuation the individual places on the next preferred plan. We analyze the behavior of a plan which regards the behavior of all other plans as given, so that $\bar{u}_i$ can be regarded as fixed. Given m_i and $\bar{u}_i$, individual i chooses the plan if:

$$\mu_i > \bar{u}_i - v_i(m_i).$$

For now, we assume that, for each i, the plan has exactly the same information as individual i regarding the individual's service-related valuation of its services, v_i, and regarding the utility from the next preferred plan, $\bar{u}_i$. For each individual i, the plan does not know the true value of u_i but it knows the distribution from which it is drawn. Therefore, for a given m_i and $\bar{u}_i$, the probability that individual i chooses the plan, from the point of view of the plan is:[4]

$$n_i(m_i) = 1 - \Phi_i(\bar{u}_i - v_i(m_i)). \tag{2}$$

Managed Care

Managed care rations the amount of health care a patient receives without the use of demand-side cost sharing, and thus without imposing financial risk on enrollees. Two approaches have been employed to model the rationing process. In an early model of managed care, Baumgardner's (1991) plan sets a common quantity of care for persons with the same illness but who differ in severity, an approach later employed by Ramsey and Pauly (1997). Both of these papers consider only a single illness and are concerned with the properties of quantity rationing compared to demand-side cost sharing for purposes of controlling moral hazard. Ramsey and Pauly (1997) show that some quantity setting is always part of the optimal combination of demand-side cost sharing and rationing. Glazer and McGuire's (1998) plans also set quantity in a two-illness model focused on adverse selection. They characterize equilibrium in the insurance market with managed care to solve for the optimal risk adjustment policy to counter selection incentives.[5] An alternative approach to modeling managed care, used by Keeler, Newhouse and Carter (1998), is to regard the plan as setting a "shadow price" -- the patient must "need" or benefit from services above a certain threshold in order to qualify for receipt of services. In Keeler et al. (1998), demand is for one service, "health care", and the plan

[3] This part of the utility function is similar to the set-up in Glazer and McGuire (1998).

[4] An alternative interpretation is that index i describes a group of people with the same $v_i(m_i)$ function and $n_i(m_i)$ is then the share of this group that joins the plan.

[5] The optimal risk adjustment policy anticipates the nature of the insurance market equilibrium. This will, in general, require a regulator to "overadjust" on observables (age, sex) correlated with health care costs.

sets just one shadow price.[6] Here, we adopt the shadow-price approach to managed care but allow for many services in order to study selection incentives.[7]

Let q_s be the service-specific shadow price the plan sets determining access to care for service s. A patient with a benefit function for service s of $v_{is}(\bullet)$ will receive a quantity of services, m_{is} determined by:

$$v'_{is}(m_{is}) = q_s. \tag{3}$$

Let the amount of spending determined by the equation above be denoted by $m_{is}(q_s)$. Note that (3) is simply a demand function, relating the quantity of services to the (shadow) price in a managed care plan. See Figure 1.

The use of a shadow price as a description of rationing in managed care permits a natural interpretation of the division of responsibility between the "management" of a plan, presumably most interested in profits, and the "clinicians" in a plan who face the patients. Cost conscious management allocates a budget for a service. Clinicians working in the service area do the best they can for patients given the budget by rationing care so that care goes to the patients that benefit most. In this environment, management is in effect setting a shadow price for a service through its budget allocation. It is evident in data that individuals with the same disease get different quantities of service. The constant shadow price assumption is consistent with managed care rationing but with more care being received by patients who "need" it more.[8]

[6] In Keeler et al. (1998) plans are characterized by a single price, but do not choose its level. Plans do not choose premiums or level of care and are thus inactive in terms of selection.

[7] Quantity setting and shadow price methods of rationing correspond closely to Mechanic's (1997) distinction between "explicit" and "implicit" rationing mechanisms. For a given demand or marginal benefit schedule, the choice of a shadow price is of course equivalent to quantity setting.

[8] In this way the shadow price approach seems superior to the quantity setting approach in a context of a distribution of demands for a service. The shadow price method is also the "efficient" way to ration a given budget. There are other suppositions about how physicians ration care. For example, some have proposed that the sickest get more care regardless of expected benefit.

Profit and Profit Maximization

Let $q = \{q_1, q_2, \ldots, q_s\}$ be a vector of shadow prices the plan chooses and $m_i(q) = \{m_{i1}(q_1), m_{i2}(q_2), \ldots, m_{is}(q_s)\}$ be the vector of spending individual i gets by joining the plan. Define $n_i(q) \equiv n_i(m_i(q))$. Expected profit, $\pi(q)$, to the plan will depend on the individuals the plan expects to be members, the revenue the plan gets for enrolling these people, and the costs of each member.

$$\pi(q) = \sum_i n_i(q)[r_i - \sum_s m_{is}(q_s)] \tag{4}$$

where r_i is the (possibly risk-adjusted) revenue the plan receives for individual i. The plan will choose a vector of shadow prices to maximize expected profit, (4). Define $\pi_i(q)$ to be the gain or loss on individual i:

$$\pi_i(q) = r_i - \sum_s m_{is}(q_s) \tag{5}$$

Given this, for one such service s (dropping the arguments q and q_s from all functions), the condition for profit maximization is:

$$\frac{d\pi}{dq_s} = \sum_i [(\frac{dn_i}{dq_s})\pi_i - n_i m'_{is}] = 0 \tag{6}$$

Condition (6) has two parts. Consider the term $-n_i m'_{is}$. If the shadow price q_s is raised, the plan will spend less by m'_{is} on individual i if he joins the plan. This term is always positive, reflecting the savings the plan can achieve by rationing more stringently. The other term, $\frac{dn_i}{dq_s}\pi_i$, may be positive or negative for any individual. $\frac{dn_i}{dq_s}$ is always negative, reflecting the fact that everyone will find the plan somewhat less attractive as q_s is raised. The π_i will be positive or negative, depending on whether the risk-adjusted revenue is above or below the costs the individual will incur given the rationing in the plan. The idea behind competition among managed care plans is that the first term must after summation be negative -- the plan by rationing too tightly will lose profitable customers -- to balance the plan's incentive to reduce services to the existing enrollees.

To see what (6) implies for various services, we make some substitutions. The change in the probability of joining can be written as the product of two derivatives:

$$\frac{dn_i}{dq_s} = \frac{dn_i}{dv_{is}} \frac{dv_{is}}{dq_s}. \tag{7}$$

From (2), $\frac{dn_i}{dv_{is}}$ is simply Φ'_i, and from (1) and (3), $\frac{dv_{is}}{dq_s}$ is $q_s m'_{is}$. Assuming that the elasticity of demand for service s is the same for all individuals at every q, and denoting this elasticity by e_s, we get:

$$m'_{is} = \frac{e_s m_{is}}{q_s}, \tag{8}$$

for every i. Note that the assumption that for every shadow price q_s the elasticity of demand for service s is the same for all individual s does not imply, of course, that all individuals have the same demand curve for that service. It only implies that demand curves of different individuals, for a certain services, are "horizontal multiplications" of some "basic" demand function for the service. Individuals will differ in their relative demands. One interpretation of this assumption, as in Glazer and McGuire (1998), is that given someone is sick, a common function describes valuation of a service, but people differ in the probability that they become ill.

Substituting for m'_{is} from (8), we can rewrite (6) as:

$$\sum_i [\Phi'_i \, e_s m_{is} \pi_i - \frac{n_i e_s m_{is}}{q_s}] = 0. \tag{9}$$

Multiplying through by $\frac{q_s}{e_s}$ and summing the terms separately,

$$q_s \sum_i \Phi'_i \, m_{is}\pi_i - \sum_i n_i m_{is} = 0, \text{ or}$$

$$q_s = \frac{\sum_i n_i m_{is}}{\sum_i \Phi'_i \, m_{is}\pi_i} \tag{10}$$

From (10) we can make some observations about q_s in profit maximization. The numerator of (10) reflects the incentive the plan has to save money on its expected enrollees. The greater is the numerator, the larger will be q_s. The denominator describes the expected gains a plan sacrifices by losing enrollees. The denominator contains a product $m_{is}\pi_i$, weighted by the change in enrollment probability, Φ'_i. Some enrollees will be profitable, with $\pi_i > 0$ given the risk adjustment formula in use, and some will be unprofitable, with $\pi_i < 0$. The association between these gains and losses and spending will determine the value of the denominator.

For any service provided in profit maximization, the denominator of (9) must be positive, implying that in profit maximization, provision of all services on average attracts profitable enrollees. This observation echoes a conclusion from the health care payment literature where under prospective payment systems, the enrollment response, or more generally, demand response, induces a provider to supply a noncontractible input (corresponding here to q_s). See Rogerson (1994), Ma (1994), or Ma and McGuire (1997). Creating profits on the margin in this way to induce firm "effort" is inconsistent with zero profitability unless marginal costs are less than average costs or the payer uses a two-part tariff of some kind to reimburse the provider.

In a first-best allocation, a payer or regulator would induce the plan to set $q_s = 1$, leading to an equality between the marginal benefit of spending on a service and its marginal cost. Equation (10) shows how a payer could do this for this one service by manipulating the payment r_i. For a given level of payment r_i, if q_s were too high, for example, the payer could simply increase r_i by some factor, paying more for every potential enrollee. That would raise the denominator of (10) and induce more spending. In the one service case, risk adjustment is not necessary, simply paying more for all enrollees will do. As Glazer and McGuire (1998) point out, if plan quality were one dimensional, the right quality could be induced by simply paying more per person, without regard to risk adjustment. Changing the risk adjustment formula, for a given overall level of spending, will also affect q_s by changing the product of $m_{is}\pi_i$. If, for example, people with high levels of spending on service s are also those with high levels of spending on other services, then by altering the risk adjustment formula so as to pay more for high users and less for the others, the incentives to set q_s high may be reduced.

Uncertainty

So far we have assumed that each individual i knows with certainty his valuation of each of the s services $v_{is}(m_{is})$, and, hence, given some q, the dollar amount of the different services that will be provided to him upon joining the plan. In order to make our model more realistic and to prepare for empirical application, we shall now allow for each individual to be uncertain about his future demands for the different services. Let us suppose that each individual has a set of prior beliefs about his possible health care demands, and that the plan shares these beliefs.

Let T denote the set of possible health states of each individual and let t denote an element of T. Let $v_t = \{v_{t1}(m_{t1}), v_{t2}(m_{t2}), \ldots, v_{ts}(m_{ts})\}$ denote the vector of S valuation functions for the S services, if the health state is realized to be t. We assume that for each t and s, $v_{ts}()$ satisfies the properties discussed earlier.

Upon joining the plan, each individual i is uncertain about his health state t, and he has some prior distribution f_i over the set of possible states. The individual's prior distribution f_i represents what the individual believes about his health states. Momentarily we will focus on one individual and hence will drop the subscript i from the notation.

Let $\tilde{x}_t$ be some random variable, the value of which depends on the state t, and let f be a distribution function defined over T. Let $E_f[\tilde{x}_t]$ denote the expected value of $\tilde{x}_t$ with respect to the distribution f.

The order of moves in this modified model is as follows: first, the plan chooses its level of shadow prices $q = (q_1, q_2, \ldots, q_s)$, then the individual chooses whether or not to join the plan (in a manner studied below), and finally the individual's health state is realized and services are provided.

We assume that when services are provided, the individual's "true" health state is already known. Hence, for a given shadow price q_s and a valuation function v_{ts}, the plan's expenditures on this individual on services s will be $m_{ts}(q_s)$, given by:

$$v'_{ts}(m_{ts}(q_s)) = q_s.$$

Let $v_t(q) = \sum_s v_{ts}(m_{ts}(q_s))$

If the individual joins the plan, his expected utility is: $\mu + E_f[v_t(q)]$. Note that unlike his health state, we assume that μ is known to the individual when choosing the plan.

Let $\bar{u}_t$ denote the individual's utility if his health state is t and he chooses the alternative plan. Thus, $E_f[\bar{u}_t]$ is the individual's expected utility if he chooses the alternative plan.

We assume no asymmetry of information between the plan and the individual regarding the individual's health state. Thus, the plan knows the individual's prior beliefs, f, about his future health state. The plan, however, does not know the true value of μ and it holds beliefs $\Phi(\mu)$ about its cumulative distribution.

Thus, for a given shadow price q, the plan's assigned probability that the individual will join the plan if his prior beliefs about his future health state are given by f_1 is:

$$n_f(q) = 1 - \Phi(E_f[\bar{u}_t - \tilde{v}_t(q)]). \tag{2'}$$

The plan's expected profit on the individual is:

$$\pi_f(q) = n_f(q)(r - E_f[\sum_s \tilde{m}_{ts}(q_s)]). \tag{5'}$$

Differentiating the above with respect to $q_{s'}$ we get:

$$\frac{d\pi_f(q)}{dq_{s'}} = \Phi' E_f[\tilde{v}'_{ts}\, \tilde{m}'_{ts'}](r - E_f[\sum_s \tilde{m}_{ts}]) - n_f E_f[m'_{ts'}] \tag{6'}$$

Using the fact that $v'_{ts} = q_s$ for all t, and assuming that $m'_{ts} = \frac{e_s m_{ts}}{q_s}$ for all t, we get that the right-hand side of (6') becomes:

$$e_{s'}(\Phi' \hat{m}_{s'}(r - \sum_s \hat{m}) - \frac{n_f \hat{m}}{q_{s'}}) \text{ where } \hat{m} = E_f[\hat{m}].$$

We can now show how the plan chooses its profit maximizing shadow prices in this case. Assume a population of N individuals. Each individual i has some prior beliefs f_i over the set of possible health states. Setting (6') equal to zero, the profit maximizing q_s will be:

$$q_s = \frac{\sum_i n_i \hat{m}_{is}}{\sum_i \Phi'_i \hat{m}_{is}(r_i - \sum_{s'=1,\dots,s} \hat{m}_{is'})} \tag{10'}$$

where $\hat{m}_{is} = E_{fi}[\tilde{m}_{ts}]$ is individual i's *predicted* expenditures on services s, where the prediction is with respect to the individual's prior beliefs about his future expenditures on service s. Define

$$\hat{\pi}_i = r_i - \sum_{s=1,\ldots,S} \hat{m}_{is} .$$

To investigate which shadow prices are set high relative to other shadow prices, we use (10') to construct a ratio of q_s to $q_{s'}$ where s' is some other service. We simplify by abstracting from individual differences in enrollment response by assuming that $\Phi'_i = \Phi'$. This amounts to saying that an increase in the value of plan i increases the likelihood of joining for all individuals equally. Equation (10') can now be used to write the ratio of two shadow prices, q and q'. Note that the Φ' term cancels out of this expression:

$$\frac{q_s}{q_{s'}} = \frac{\Sigma_i \hat{m}_{is'} \hat{\pi}_i \Sigma_i n_i \hat{m}_{is}}{\Sigma_i \hat{m}_{is} \hat{\pi}_i \; \Sigma_i n_i \hat{m}_{is'}} \tag{10''}$$

There is no particular reason to expect (10") to be equal for all service pairs unless the risk adjustment system is so good as to equalize the relative incentives to supply each service.

The Effect of Individuals' Information

Information plays an important role in creating distortions of adverse selection. We are now ready to study how individuals' information (beliefs) about their future health care needs affect the plan's profit maximizing shadow prices. Let

$$\hat{m}_s = \frac{\sum_i \hat{m}_{is}}{N} \qquad\qquad r = \frac{\sum_i r_i}{N}$$

$$\hat{\sigma}_s = \sqrt{\frac{\sum_i (\hat{m}_{is} - \hat{m}_s)^2}{N}} \qquad\qquad \sigma_r = \sqrt{\frac{\sum_i (r_i - r)^2}{N}}$$

$$\hat{\rho}_{s,s'} = \frac{\sum_i (\hat{m}_{is} - \hat{m}_s)(\hat{m}_{is'} - \hat{m}_{s'})}{N \hat{\sigma}_s \hat{\sigma}_{s'}} \qquad\qquad \hat{\rho}_{rs} = \frac{\sum_i (r_i - r)(\hat{m}_{is} - \hat{m}_s)}{N \hat{\sigma}_s \sigma_r}$$

$$\hat{M} = \sum_{s=1,\dots,S} \hat{m}_s$$

and assume that $n_i = n$, and $\Phi'_i = 1$ for all i. Equation (10') can, then, be written as

$$q_s = \frac{n\hat{m}_s}{(r\hat{m}_s + \hat{\rho}_{rs}\hat{\sigma}_s\sigma_r) - (\hat{\sigma}_s^2 + \sum_{\substack{s'=1,\dots,S \\ s'\neq s}} \hat{\rho}_{s,s'}\hat{\sigma}_s\hat{\sigma}_{s'} + \hat{m}_s\hat{M})} \tag{11}$$

The effect of an individual's information on the choice of q_s enters through $\hat{\sigma}_s$. Suppose, initially, that all individuals are identical in their beliefs about their health care needs of all services for the coming period. In such a case, $\hat{\sigma}_s = 0$ for all s and $q_s = \frac{n}{r - \hat{M}}$ for all s. Thus, in this case all shadow prices are the same and no distortion is obtained. This result is independent of the risk adjustment system and of correlation of predicted spending for different illnesses.

Suppose, now, that individuals have some information that makes them differ from each other with respect to their beliefs about their need of some service s. In such a case, $\hat{\sigma}_s > 0$. Suppose that there is no risk adjustment, so $r_i = r$. We can see that the more heterogeneous are individuals with respect to their $\hat{m}_{is}$, the larger will be $\hat{\sigma}_s$ and the higher will be the shadow price q_s. This is the standard adverse selection result. The better the information that individuals have about their future needs, the bigger will be the distortion created by the plan in order to attract the profitable individuals.

The effect of correlation among spending on different services on the shadow price can also be observed in (11). If needs are not at all correlated, then $\hat{\rho}_{s,s'} = 0$ and the only effect on the shadow price comes from individuals' information $\hat{\sigma}_s$. If, however, needs are correlated, $\hat{\rho}_{s,s'} > 0$ and the larger $\hat{\rho}_{s,s'}$ the higher will be the shadow price of services s and s'. Risk adjustment can counter these forces. The larger is the correlation between predicted spending on service s and risk adjustment payment, $\hat{\rho}_{r,s}$, the higher will be the denominator of (11), and the lower the shadow price.

III. Measuring Shadow Prices: An Empirical Illustration

In this section we illustrate how to use our measure. As we noted in the introduction, the data we will use are from an "unmanaged" plan, so the findings can not be regarded as definitive. Our purpose here is to illustrate how to use presently available data to calculate the distortion index. At the same time, the elements that feed into incentives to distort, such as predictability of various services, and correlation among use in various categories of service, are likely to be largely common to managed and unmanaged patterns of care. We believe our findings are therefore of some interest in themselves.

The empirical building blocks for estimation of shadow prices are the expected spending of individuals by service class and the correlation of expected spending across services and under differing information assumptions (see equation (11)). Our estimation strategy is aimed at obtaining estimates of future spending, conditional on the information assumptions, which minimize the forecast error. The performance of a number of estimation strategies for health care spending data have been assessed over the past fifteen years. Duan et al. (1983, 1984) and Manning et al. (1981) contend that two-part models minimize mean forecast errors under distributional assumptions commonly exhibited by health spending data. Two-part models consist of one equation, typically a logit, for the yes/no decision about use, and a second equation, typically estimated by OLS, describing the extent of use, given some use. We use a two-part model for estimation under differing information assumptions. An "informational assumption" means, operationally, which covariates to include in the models. The pieces of equation (11) are computed from the predicted values generated from these estimated models.

Data

The data are health claims and enrollment files from the Michigan Medicaid program for the years 1991-1993. We chose a subset of the data for application of our model. The sample consists of individual adults who were eligible for Medicaid in 1991 through the Aid to Families with Dependent Children (AFDC) program, and who were continuously enrolled in this or another Medicaid program through the end of 1993. We excluded individuals who joined an HMO during the study time period. The resulting sample consisted of 16,131 individuals, overwhelmingly female (90.5%), with a mean age of 32 years.

Defining Services

There are a variety of approaches one could take to identifying "services," ranging from very specific treatments, such as angioplasty, to groups of treatments which would be associated with an illness, such as care for hypertension. In this paper we define a "service" as all the treatments received in connection with certain diagnostic classifications. We identify 9 classes of services: 1) birth related, 2) cancer care, 3) gastrointestinal problems, 4) heart care, 5) hypertension, 6) injuries/poisonings, 7) mental health/substance abuse, 8) musculoskeletal problems, and 9) an "all other category." Each of the services is defined by a grouping of ICD-9-CM diagnostic codes.[9] We chose conditions that met several criteria. Significant shares of the enrolled population received treatment for each condition. The categories were broad enough so that at least 7.5% of the population was treated for each condition in a year. We included conditions that were a mix of chronic (cancer, hypertension, metal health care) and acute

[9] Appendix A shows classification of services by ICD-9 codes.

conditions (gastrointestinal, injuries, and birth-related). Treatments for some conditions are likely to be expensive, some much less so. Together, the seven conditions examined account for about 46% of all spending. Some treatments for included conditions are arguably quite predictable, such as birth-related spending, while others might be considered more random, such as injuries and poisonings. We classify all health care claims according to the primary diagnosis attached to the claim.

Patterns of Spending

Table 1 provides an overview of the patterns of utilization across the service types identified. By and large utilization of different service types is relatively stable over the three years observed. The most notable change is the reduction in the share of people with birth related spending. In 1991, 25.7% of the sample had birth-related spending compared to 16.7% in 1993. Birth of a child may have initiated a period of eligibility for some of these women, accounting for the elevated rate in the first year.

Table 2 describes patterns of utilization and spending for the sample in 1993. Birth related spending has the highest expected level of spending of all the listed conditions ($653) or 19.2% of total spending. Most of the other conditions have expected spending levels of $126 to $250 or between 3% and 7% of total spending.

The sixth and seventh columns of Table 2 give an indication of the correlation of spending on a service with spending on other types of care, and of predictability, key elements of the formula for shadow prices (11). The sixth column reports the correlation between spending on each of our nine service categories and the sum of spending on all other services. In general, these correlations are quite low. None of the eight service-specific correlations exceed 0.20, with the exception of the "other" category. Gastrointestinal care, cancer care and treatment of injuries and poisonings have the highest correlation with all other types of spending. Correlation with spending in the previous year for each category indicates persistence of spending. Persistent spending is probably more predictable. Several of the illness thought to be more chronic in character, hypertension, mental health/substance abuse and musculoskeletal conditions, display relatively high correlations in service-specific spending over time. Mental health spending has the highest year-to-year correlations.

Estimation of Components of the Ratio of Shadow Prices

Risk Adjusted Premiums: We first calculate the premium assuming that a single payment is made for all enrollees. This premium is based on the simple average level of spending across all enrollees and corresponds to a case with no risk adjustments. We next construct two sets of true "risk adjusted" premiums, one based on the Ambulatory Diagnosis Group (ADG) classification system (Weiner et al., 1996,) and one based on the DCG classification system (Ellis et al., 1996).[10] In each case we adjusted the risk adjustment upward to make the marginal profit per enrollee positive on average, as it must be if plans are to be induced to compete for enrollees by service quality.

Expected Spending: The variable $\hat{m}_{is}$ is the expected level of spending by each individual for each category of service. Estimating expected spending requires assumptions about the information available to individuals. The literature reflects a wide range of conceptions of what consumers might know about their health risks. Newhouse et al. (1989) suggest that individuals know all the information contained in measurable aspects of health status plus the time invariant-person specific component of the unobserved factors contributing to

10 We used publicly available algorithms to implement these risk adjustment systems. The ADG algorithm is the 1997 version of the software provided by Jonathan Weiner at Johns Hopkins University. The HCC algorithm is the 1997 version of software provided by Randy Ellis of Boston University.

variation in health care spending. Welch (1985) makes a similar assumption, referring to a "permanent" component of health spending that is individual-specific. Welch speculates that individuals might know more than this and be able to forecast use of some acute services such as births and some other illnesses. Some empirical work on plan choice confirms the presence of considerable individual knowledge. Ellis (1985) and Perneger (1995) show that an individual's historical pattern of spending affects health plan choice. Other research points to the fact that individuals appear to select plans on the basis of information not contained in risk adjustment systems (Cutler, 1994; Ettner et al., 1998).

We consider the implications of several informational assumptions. Recall that if individuals can predict nothing, there is no selection problem, so no simulation needs to be done for this case. We start with the assumption that individuals can predict based on age and sex. That is, we assume each individual predicts they will use the average of a person of their age and sex for each service category. Alternatively, we assume individuals can use the information contained in prior use. As will be seen shortly, if individuals know all the information contained in prior use, existing risk adjusters cannot cope with the selection-induced inefficiencies, and some services would have very high or very low q's in profit maximization. In the simulations, we therefore equip individuals with some of the information in prior use, 10%, 20%, 30% and 40%, to show the impact of more information. In order to construct these estimates under different information conditions, we estimate a series of two-part models. Each two-part model uses right hand side variables (e.g. age and sex) at their 1991 values to explain service specific spending in 1992. Variables included in the model correspond to information individuals are assumed to be able to use to predict spending. We estimate two sets of regressions, one with age and sex as right-hand variables and one with age, sex, and prior spending. The estimated coefficients from each pair of service specific regressions are then applied to 1992 values of the right hand side variables to generate estimates of expected spending for each individual.

Following Duan et al. (1983) and Manning et al. (1981), each two-part model is specified as:

$$\text{logit (Pr (Spending on service s} > 0))_i = \beta'_1 X_i + \varepsilon_{i1} \tag{12}$$

$$\sqrt{(\text{Spending on service s} \mid \text{spending} > 0)_i} = \beta'_2 X_i + \varepsilon_{i2} \tag{13}$$

where i indexes the individual enrollee, X is a vector of individual characteristics (either age, sex, or age, sex, and prior use), β is a vector of coefficients to be estimated and ε is a random error term. Equation (12) is a logit regression. Equation (13) is a linear regression that estimates the impact of the Xs on the square root of the level of spending on each service for individuals with positive spending on that service. We chose the square root transformation to deal with skewness in the distribution of spending rather than the more common logarithmic transformation because the smearing estimator for the square root model is less sensitive to heteroskedasticity than the log transformation.[11] The difficulties in retransformation in the context of the two-part model have been treated in detail by Manning (1998) and Mullahy (1998). In those papers, it is shown how sensitive expected spending estimates can be to distributional properties such as heteroskedasticity. The use of a transformation to account for skewness in the spending data necessitates use of the "smearing" estimator to retransform the

[11] We tested for heteroskedasticity using the Breusch-Pagan test and rejected homoskedasticity. Moreover, the heteroskedasticity was not a simple function of any right hand variable such as previous spending.

predicted values of spending to the expected levels of spending consistent with the original distributions of spending (Duan et al., 1983). Since this application calls for predicting 1993 spending using 1992 data and coefficients from the two part model of 1992 spending on 1991 right side variables, the smearing factor is taken from the error term of the 1991-1992 regressions. Since we use a square root transformation, the smearing factor is additive as opposed to the multiplicative form in the case of the logarithmic transformation. The resulting empirical analysis consists of a set of 18 regressions for each of the two informational assumptions we make.

Plan Enrollment: We assume that competing managed care plans are in a symmetric equilibrium, and the plan therefore enrolls a representative sample of the population. To estimate plan spending on each service, the $\sum_{is} n_i m_{is}$, in the numerator of (10), we will simply use the average spending in the sample.

Regression Results

We summarize the predictions of the 18 two-part models in Table 3 by reporting the correlations between actual and predicted service specific spending levels. This correlation is negatively and monotonically related to the absolute prediction error of the spending model. As expected, correlations between actual and predicted spending are generally quite low for all services when only age and sex related information is known by consumers. The birth-related correlation between actual and predicted spending is, however, relatively large at 0.21. With prior use, the correlation between predicted and actual spending improves markedly for most services. For example, birth, mental health, hypertension and gastrointestinal conditions all had relatively high correlations between actual and predicted spending when consumers are assumed to know prior level of service specific spending (0.216, 0.306, 0.227 and 0.184 respectively).

Shadow Prices

The shadow prices implied by individuals' predictions and a risk adjustment policy are contained in Table 4. Three information assumptions are combined with three risk adjustment policies to produce nine sets of profit-maximizing shadow prices. The q for the "other" category is normalized to 1.00 in all cases, so each entry in the table needs to be read as the shadow price relative to this numeraire.

Begin with the first three columns of results, computed for the assumption that individuals can forecast health costs based only on their own age and sex. The very first column shows the consequences of no risk adjustment with this informational assumption. Individuals cannot forecast very well at all, so the incentives plans have to distort are small, even with no risk adjustment. All estimated q's are close to 1.00 with the exception of birth-related expenditures. Birth-related expenses are more predictable with age and sex, so plans will have an incentive to ration these services more tightly. Interestingly, the two risk-adjustment systems tested, ADGs and HCCs, each exacerbate the distortion in birth expenses.Apparently the risk adjusted payments under these systems are relatively less correlated with the predictable expenses, and magnify plans' incentives to discriminate against these categories of expenditures.

The second set of three columns reports q's when individuals can predict based on 25 percent of the information contained in prior spending. Specifically, predicted spending for each person was figured as a weighted average of the prediction based on age-sex and the prediction based on age, sex, and prior year spending in that category. When we say "can predict based on 25% of the information contained in prior spending," we mean, operationally, that the weight on the prior spending prediction is 25%, and the weight on the age-sex prediction is 75%.

Estimated q's diverge quite a bit from 1.00 when individuals know only 25% of the information contained in prior use and there is no risk adjustment. The highest estimated q is mental health and substance abuse; three categories are together for the lowest. Recall that the q's presented here are relative to the numeraire. "Other" services too might be distorted, and indeed, in this case it is evident that other services with their q of 1.00 are above the average q for all services.

The third panel of three columns presents calculated q's, assuming individuals can predict spending based on forty percent of the information contained in prior spending. Note that with no risk adjustment, mental health and substance abuse services are quite distorted as evidenced by the q of 3.73. Figure 2 graphs these results. Risk adjustment attenuates the distortions, moving all q's toward unity. The mental health and substance abuse are continues to have the largest service-specific q.

The two risk adjustment systems studied, ADGs and HCCs, have very similar effects on incentives. For some services, notably birth-related expenditures, risk adjustment improves matters, moving the profit-maximizing q closer to the overall average. But a favorable effect of risk adjustment is not uniform. The incentives to overprovide care for hypertension are exacerbated by risk adjustment. Mental health and substance abuse changes from a service that tends to be underprovided to one much closer to the average with either risk adjustment system. In the next section, we describe a summary index that shows that overall, risk adjustment helps, even if for some services, it makes matters worse.

As table 4 shows, the calculations for shadow prices are sensitive to how much information individuals have in making their predictions. In Figure 3 we graph the profit-maximizing q's for two services, mental health/substance abuse and musculoskeletal care as individuals know more and more of the information contained in prior use in the absence of risk adjustment. Distortions go up exponentially as information improves. In the case of the q for mental health and substance abuse, the damage from selection incentives accelerates rapidly around the 30% range. For the muskuloskeletal category the graph is smoother than in the mental health and substance abuse care. When individuals know as much as 50% of prior use, profit-maximizing q's go off the charts, signaling that incentives to over and underprovide are very strong.

These results highlight the importance of what individuals can forecast for the implications of selection incentives and risk adjustment. Individuals of course do "know" what they have used in the past; the issue is how well can they use this information to predict. Individuals cannot reasonably be expected to forecast based on population information, but on the other hand they are likely to have more private information than we give them credit in the models here. Unfortunately, there is no good way to know if the informational assumptions explored here bound what we can really expect individuals to be able to anticipate.

A Welfare Index

Results in Table 4 can be summarized in a single measure of the selection-related distortion. The welfare loss can be approximated by:

$$L = \sum_{s} 0.5(\Delta q_s)(\Delta m_s) \tag{14}$$

where Δq_s is the discrepancy between the q for service s and the second best q, and Δm_s is the change in spending induced by the discrepancy in q. For purposes of this analysis we define Δq_s as the difference between q_s and the weighted average q for all service types contained in Table 4. Thus, for each service s, we take the expenditure-weighted average q for each information/risk adjustment combination, and compute Δq_s based on that. Since Δq_s is in percentage terms, Δm_s is simply Δq_s multiplied by demand elasticity, which we assume for simplicity is 0.25 for all services. When individuals know age-sex and 25 percent of the information in prior use, the welfare loss without risk adjustment is only 1.9% of spending, and this is reduced to 1.3% by both risk adjusters.[12]

The next step in this analysis would be to find the "optimal risk adjustment." Given a set of variables available for risk adjusting, equation (14) could be minimized with respect to the weights on the risk adjusters. Conventional risk adjusters are derived from coefficients from a regression of adjuster variables on total expenditures in a population. These weights are in general not optimal from an economic standpoint. (Glazer and McGuire, 1998).

"Carve Outs"

Payers have other tools in addition to risk adjustment to deal with selection incentives in insurance. One device used by public and private payers is to "carve out" an area of the benefit, and separate this from the main insurance contract. For example, mental health and substance abuse benefits are often carved out, meaning that the regular health plan chosen by the enrollee is not responsible for providing mental health and substance abuse care. A separate managed care company specializing in this area of care receives a contract from the employer or other payer to provide this benefit. Carve outs can be done for reasons of controlling moral hazard or moderating selection incentives (Frank and McGuire, 1998). Our analysis shows how this might happen. A profit-maximizing plan might distort the shadow price for service s' to affect its

[12] This welfare index is for a single firm. A number of papers have looked at the case in which plans differ in two dimensions, price and "generosity." Cutler and Reber (1997), Cutler and Zeckhauser (1997) and Keeler et al. (1998) emphasize distortions in consumer plan choice when prices are set by an employer or government in a way that does not reflect consumers' additional costs in more generous plans. High-demand individuals find the price difference worth paying, stampede to the most generous plan, and threaten the viability of plan choice. Cutler and Reber (1997) calculate that the welfare cost of this selection-related inefficiency to be 2-4 percent of health care costs in the case of one employer. As Pauly (1985) pointed out, however, one could lay this inefficiency at the feet of regulation, not adverse selection. If plan premiums were set in a market and not regulated, prices would reflect expected costs, and in the absence of asymmetric information, there would be no distortion in plan choices.

enrollee profile. If any service is carved out, this strategy will change. In particular, if service s' is carved out, rationing strategies for all other services will generally be affected. Carving out any one service will affect the efficiency of that service provision as well as the nature of insurance market equilibrium overall.

Our model allows us to examine these effects. In this section we report illustrative results of carving out three services from the main insurance contract. We recalculate the profit-maximizing q's in the case of carving out each service. The most commonly carved out service is mental health and substance abuse (known together as behavioral health), and we start with that. The new q's are shown in Table 5 for the case in which individuals know 25% and 40% of the information contained in prior spending and plan payments are made using the HCC risk adjustment system. Note that by comparing Tables 4 and 5 there is some effect on the q's for services other than the one that is carved out. However, the effect is generally to move the calculated q away from unity. For example, the calculated q for heart disease assuming 40% information and HCC risk adjustment is 0.33 (Table 4). When mental health and substance abuse are carved out, the calculated q falls to 0.28. Similarly, the q for mental health assuming 40% information and HCC risk adjustment is 0.76 (Table 4). When musculoskeletal services are carved out the calculated q is 0.72. Thus, while the distortion incentives for the carve-out service are reduced, distortions may increase for the services remaining in the health plan.

IV. Conclusion

Health plans paid by capitation have an incentive to distort the quality of services they offer to attract profitable and deter unprofitable enrollees. Characterizing plans' rationing as imposing a "shadow price" on access to care, we show that the profit maximizing shadow price for each service depends on the dispersion in health costs, how well individuals forecast their health costs, the correlation among use in illness categories, and the risk adjustment system used for payment. We further show how these factors can be combined to form an empirically implementable index that can be used to identify the services that will be most distorted in competition among managed care plans. A simple welfare measure is developed that measures the distortion caused by selection incentives. We apply our ideas to a Medicaid data set to illustrate how to calculate distortion incentives, and we conduct policy analyses of risk adjustment and carve out options.

Our paper is related to other recent research in applied industrial organization that begins with an explicit characterization of conditions for profit maximization and information constraints in the market. That literature has explained phenomena such as the inefficient choice of the number of product lines (Klemperer and Padilla, 1997) and entry and exit in hub and spoke networks (Hendricks, Piccione and Tan, 1997). These papers use the profit maximization conditions to explain observed equilibria that appear to deviate from simple market models.

From the a practical standpoint of in health policy, our paper shows how the incentives to distort services depend in a relatively straightforward way on means and correlations among predicted values of health care services in a population. Several interesting findings emerge from the small data set we analyze. The most striking is the importance of individuals' knowledge and their ability to forecast their health expenses. This factor has been appreciated in abstract terms in earlier writing, but the dramatic effect that information has on incentives has not been fully appreciated. As we figure it, if people know what they are sometimes commonly assumed to know (age, sex and prior spending), selection incentives would be very severe and beyond the power of existing risk adjusters to deal with. Study of what individuals can forecast is a very key area of empirical research.

We are forced in this paper to analyze hypothetical cases in which individuals are not allowed to know "too much." Within this limitation, we illustrate how in this data set, risk adjustment can be assessed and decisions about the efficiency effects of carve outs can be made. Two proposed risk adjustment systems have significant and similar effects in terms of cutting the magnitude of distortion incentives. Carve outs too can help, especially when one service seems to be the major distortion instrument, as mental health and substance abuse is in one of our scenarios.

Another point to emphasize is that the specifics of the results will vary according to the underlying patterns of use in a population. We have analyzed one relatively small data set of young women on welfare. The distortions likely to arise for the elderly or for an employed population may be quite different.

Figure 1

Determination of Spending on Service *s* for Individual *I*

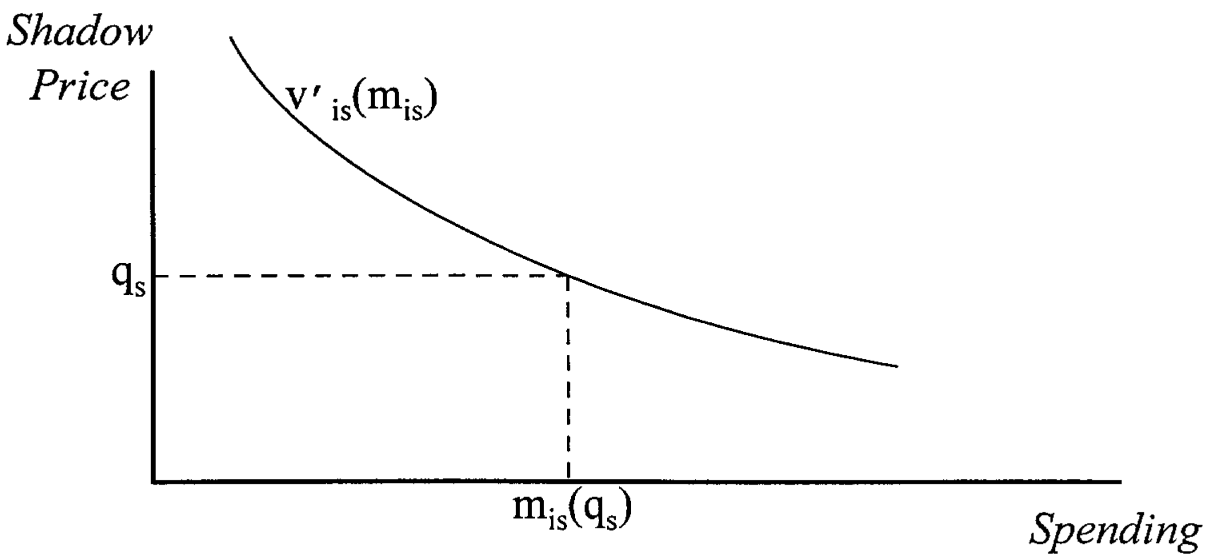

Figure 2

Shadow Prices (q's) for Various Services When Individuals Predict with 40% of Information in Prior Use

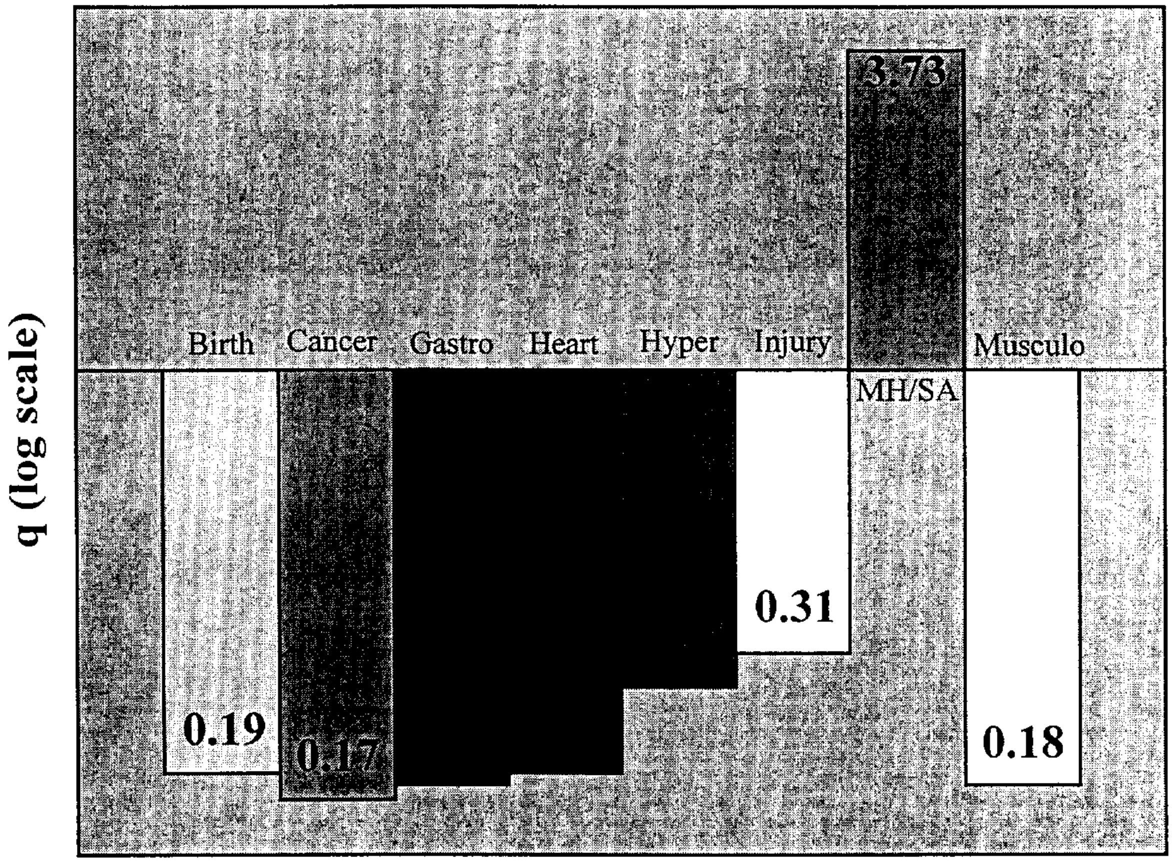

Figure 3
Shadow Price under Differing Levels of Enrollee Information

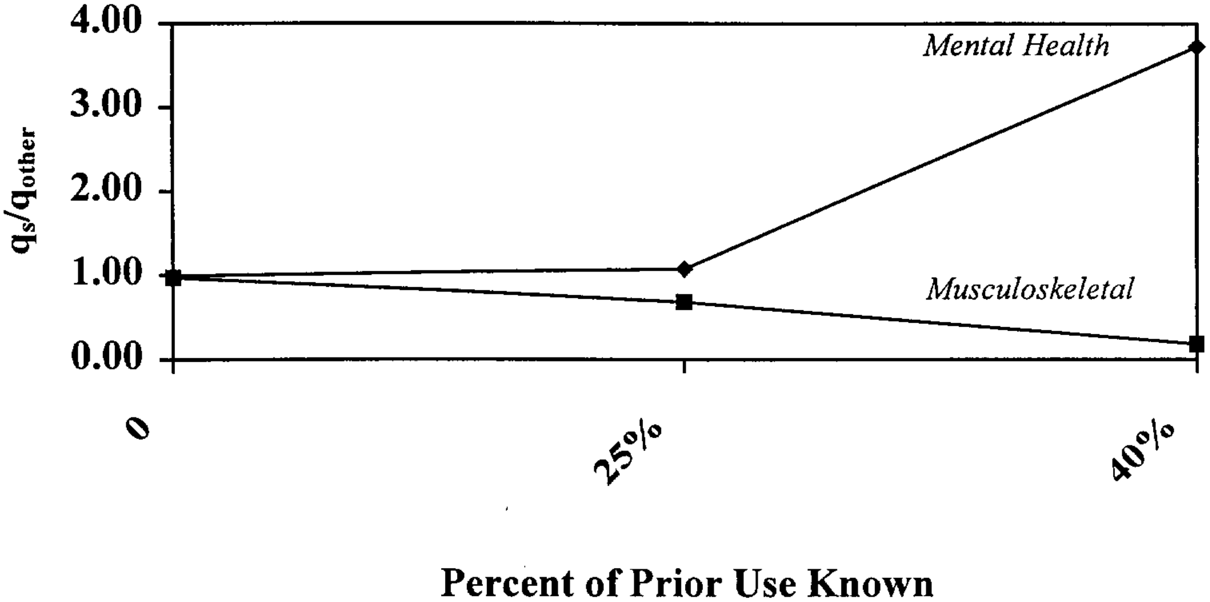

Table 1
Sample Description

N	16,131 continuously enrolled adults
Reason for Medicaid eligibility, 1991-1993	AFDC
Mean age in 1993	32.2 years (std dev=8.12)
Gender	90.5% female 9.5% male

Type of Service	Percentage of Sample Using Service Each Year		
	1991	1992	1993
Birth-related	25.7	20.6	16.7
Cancer Care	13.0	12.3	10.9
Gastrointestinal	19.2	20.8	20.4
Heart Care	8.0	7.5	7.0
Hypertension	8.2	8.3	9.3
Injuries / Poisonings	35.8	34.3	34.4
Mental Health/Substance Abuse	12.2	13.2	14.3
Musculoskeletal	27.0	29.3	30.6
Other / Missing	92.8	91.9	92.6

Table 2
Use and Cost in Michigan Medicaid AFDC 1993

Service	Probability of Any Use	Expected Charges Given Use	Expected Costs	Percent of Total Costs	Correlation with All Other Costs	Correlation with Own Costs Last Year
Birth-related	0.167	$3,904	$ 653	19.2%	0.007	0.122
Cancer Care	0.109	$1,159	$ 126	3.7%	0.155	0.127
Gastrointestinal	0.204	$1,186	$ 242	7.1%	0.167	0.166
Heart Care	0.070	$1,542	$ 108	3.2%	0.089	0.079
Hypertension	0.093	$ 249	$ 23	0.7%	0.114	0.317
Injuries / Poisonings	0.344	$ 701	$ 241	7.1%	0.189	0.033
Mental Health / Substance Abuse	0.143	$1,671	$ 239	7.0%	0.032	0.385
Musculoskeletal	0.306	$ 683	$ 209	6.1%	0.115	0.215
Other / Missing	0.926	$1,692	$1,567	45.9%	0.313	0.288

Table 3
Correlations Between Actual and Predicted Spending with Different Information Assumptions

Service	Model[13]	
	Age – Sex	**Age – Sex Prior Spending**
Birth-related	0.210	0.216
Cancer Care	0.035	0.104
Gastrointestinal	0.031	0.184
Heart Care	0.075	0.104
Hypertension	0.055	0.227
Injuries / Poisonings	0.002	0.014
Mental Health / Substance Abuse	0.019	0.306
Musculoskeletal	0.073	0.178
Other / Missing	0.052	0.099

[13] All correlations are significant at $p < 0.01$.

Table 4
Shadow Prices for Three Information Assumptions and Three Risk Adjustment Systems

	Information Assumption								
	AGE, SEX			**AGE, SEX, 25% OF PRIOR USE**			**AGE, SEX, 40% OF PRIOR USE**		
	Risk-Adjuster			*Risk-Adjuster*			*Risk-Adjuster*		
Service	None	ADGs	HCCs	None	ADGs	HCCs	None	ADGs	HCCs
Birth Related	1.15	1.25	1.23	0.77	0.91	0.95	0.19	0.35	0.43
Cancer Care	0.99	0.98	0.98	0.68	0.73	0.76	0.17	0.28	0.34
Gastrointestinal	0.99	0.99	0.99	0.69	0.73	0.77	0.18	0.29	0.36
Heart Care	1.00	0.90	0.89	0.71	0.68	0.71	0.19	0.27	0.33
Hypertension	1.01	0.87	0.87	0.80	0.62	0.61	0.27	0.26	0.28
Injuries / Poisonings	1.00	1.02	1.02	0.81	0.85	0.86	0.31	0.45	0.52
Mental Health / Substance Abuse	0.99	0.98	0.98	1.07	0.86	0.88	3.73	0.67	0.76
Musculoskeletal	0.97	0.94	0.95	0.68	0.68	0.73	0.18	0.27	0.33
Other / Missing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Weighted Average	1.026	1.040	1.036	0.884	0.902	0.919	0.818	0.664	0.703

Note: All shadow prices are relative to Other/Missing Category.

Table 5
Calculated Shadow Prices for Three Service Carve-Outs

	25% Information in Carved-Out Service			**40% Information in Carved-Out Service**		
	Service Carved Out			***Service Carved Out***		
Services	MH/SA	Heart Care	Musculoskeletal	MH/SA	Heart Care	Musculoskeletal
Birth Related	0.95	0.95	0.95	0.37	0.40	0.38
Cancer Care	0.74	0.75	0.74	0.29	0.32	0.30
Gastrointestinal	0.76	0.77	0.76	0.31	0.34	0.20
Heart Care	0.69	n/a	0.69	0.28	n/a	0.29
Hypertension	0.59	0.60	0.59	0.24	0.26	0.25
Injuries / Poisonings	0.85	0.86	0.85	0.46	0.49	0.47
Mental Health / Substance Abuse	n/a	0.87	0.87	n/a	0.74	0.72
Musculoskeletal	0.71	0.72	n/a	0.29	0.31	n/a
Other / Missing	1.00	1.00	1.00	1.00	1.00	1.00

Appendix A

1) Births
630 = ICD-9 code = 648;
650 = ICD-9 code = 676;
760 = ICD-9 code = 779;
v22 = ICD-9 code = v24;
ICD-9 code = v27, v28;
v30 = ICD-9 code = v37;
ICD-9 code = v39;

2) Cancer Care
140 = ICD-9 code = 165;
170 = ICD-9 code = 176;
179 = ICD-9 code = 208;
230 = ICD-9 code = 239;

3) Gastrointestinal
ICD-9 code = 003, 004, 008, 251, 452, 455, 555, 556, 558, 560, 562, 787;
530 = ICD-9 code = 537;
540 = ICD-9 code = 543;
550 = ICD-9 code = 553;
564 = ICD-9 code = 569;
571 = ICD-9 code = 579;
0080 = ICD-9 code = 0085;
5690 = ICD-9 code = 5695;
5710 = ICD-9 code = 5711;
ICD-9 code = 2518, 2519, 5698, 5699, 5710, 5711, 5714, 5730, 5733, 5734, 5768, 5769;
5718 = ICD-9 code = 5721;
5738 = ICD-9 code = 5745;
5760 = ICD-9 code = 5765;

4) Heart Care
390 = ICD-9 code = 398;
410 = ICD-9 code = 417;
420 = ICD-9 code = 429;
745 = ICD-9 code = 747;
ICD-9 code = 798;
4100 = ICD-9 code = 4111;
4270 = ICD-9 code = 4276;
4293 = ICD-9 code = 4299;
ICD-9 code = 4118, 4150, 4151, 4278, 4279, 4290, 4291;
ICD-9 code = 78550, 78551

Appendix A
(cont'd)

5) <u>Hypertension</u>
401 = ICD-9 code = 405;
ICD-9 code = 4372

6) <u>Injuries / Poisonings</u>
800 = ICD-9 code = 999;
E80 = ICD-9 code = E94;
E96 = ICD-9 code = E99;

7) <u>Mental Health / Substance Abuse</u>
295 = ICD-9 code = 302;
305 = ICD-9 code = 319;
ICD-9 code =293, E95, V40
3070 = ICD-9 code = 3077;
ICD-9 = 3079, 7801, 9955
ICD-9 code = 30780, 30789, 99581
ICD-9 = 291, 292, 303, 304

8) <u>Musculoskeletal</u>
710 = ICD-9 code = 739;

9) <u>Other</u>
All other ICD-9 codes

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