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Measuring adverse selection in managed health care

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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 a "shadow price" on access to various areas of care and show how the profit maximizing shadow price depends on the dispersion in health costs, individuals' forecasts of their health costs, the correlation between use in different illness categories, and the risk adjustment system used for payment. These factors are combined in an empirically implementable index that can be used to identify the services that will be most distorted by selection incentives. © 2000 Elsevier Science B.V. All rights reserved.

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1. 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). Medicaid figures are increasing rapidly. In private health insurance, about three-quarters of the covered population is already in some form of managed care, though in many cases, employers continue to bear some or all of the health care cost risk (Jensen et al., 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 capitation payment from the government or private payers for each enrollee.[2]

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.

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 is much harder for policy to address than in 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

[1] For representative discussions in the U.S. context, see Cutler (1995), Newhouse (1994), Enthoven and Singer (1995). 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 in the United States, see Holohan et al. (1995). Van de Ven and Ellis (2000) contain a recent and comprehensive review.

[2] For a recent survey of how health plans are paid in the U.S. by all major payer groups, see Keenan et al. (2000).

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 focusing 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 (2000) call it "plan manipulation." As Miller and Luft (1997, p. 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, p. 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 in others.[3] This leads, then, to the questions: How does a regulator know which services a managed care plan is skimping on or over-providing to affect risk selection? Even if the regulator did know, what could he or she do about it?

Motivated by these questions, public regulatory bodies and private payers have recently become interested in monitoring the quality of care in managed care plans. Monitoring consists of identification of measurable 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

[3] 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).

arbitrary. Quality can be too high, as well as too low, and existing approaches are all oriented to a minimum, not a maximum standard.[4] Gathering information on many standards for many plans in a timely fashion is very expensive. Plans do not all have adequate administrative capability (Gold and Felt, 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. Once costs are normalized, we can compare shadow prices across services. 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 to some numeraire service to create a "distortion index."

The shadow price is a device to capture the myriad of strategies a plan uses to ration care, other than by demand-side cost sharing (literal prices). Shadow prices can reflect plan decisions about capacity in various service areas, such as the number of specialists in a physician network or the number of staff hired in a plan department. They could reflect the makeup of networks or payment to providers, including supply-side cost sharing or the stringency of utilization review.

After developing the shadow price measure of selection distortions and discussing the properties of services that will be over and underprovided (Section 2), we illustrate how these shadow prices can be calculated with data from a health plan (Section 3). 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.

[4] This paper discusses selection-related incentives that could lead to quality for various services to be too high or too low. Another well-established argument from health economics also applies to the health insurance options considered here. The federal tax subsidy provided through the tax-free employer contribution to employee health insurance may lead to too high quality across the board.

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. However, since hypothesized competitive prices cannot be easily observed, more common is an indirect approach: estimate each firm's elasticity of demand. Following Lerner (1934), we could use demand 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 under the assumption that the firm maximizes 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 exactly 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 based on 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 in the period immediately prior to joining, and had a lower mortality rate in the period after joining (see also Eggers and Prihoda, 1982; Garfinkel et al., 1986; Brown et al., 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, 1998; Cutler and Zeckhauser, 2000; Glied et al., 2000; Robinson et al., 1993; Luft and Miller, 1988).

Risk-adjustment of payments to managed care plans is intended to counteract incentives to distort services. The basic idea behind risk adjustment is the following: If plans are paid more for enrollees likely to be costly, the plan will not shun these enrollees. Individuals choose plans based on 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.[5] We will show below, how risk adjustment works to affect plans' incentives to detect service quality in order to affect the risks the plan draws in a population.

2. 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 choose 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.

2.1. 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: $\boldsymbol{m}_i = \{m_{i1}, m_{i2}, \dots, m_{iS}\}$. The value of the benefits individual i gets from the plan, $u_i(\boldsymbol{m}_i)$, is

[5] 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 investigate how much of the variance is explained by these covariates. In the most well-known of these studies, Newhouse (1989) assumes that individuals know the information contained in their individual time invariant contribution to the variance and the autoregressive component of their immediate past spending. With these assumptions individuals can predict about a quarter of the variance. He 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% of total variance; proposed refinements improve the explanatory power considerably, but only to about 9% (Ellis et al., 1996; 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.

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,

$$u_i(\boldsymbol{m}_i) = v_i(\boldsymbol{m}_i) + \mu_i \tag{1}$$

where,

$$v_i(\boldsymbol{m}_i) = \sum_s v_{is}(m_{is})$$

The term 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. The term $v_{is}(\cdot)$ is the individual's valuation of spending on service s, also measured in dollars, where $v_{is}' > 0$, $v_{is}'' < 0$. For now, we proceed by assuming that the individual knows $v_i(\boldsymbol{m}_i)$ with certainty. Later, we consider the case when the individual is uncertain about his $v_i(\boldsymbol{m}_i)$. 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 as 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 $\boldsymbol{m}_i$ and $\bar{u}_i$, individual i chooses the plan iff:

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

For now, we assume that, for each i, the plan has exactly the same information as individual i about the individual's service-related valuation of its services, v_i, and the utility from the next preferred plan, $\bar{u}_i$. For each individual i, the plan does not know the true value of μ_i but it knows the distribution from which it is drawn. Therefore, for a given $\boldsymbol{m}_i$ and $\bar{u}_i$, the probability that individual i chooses the plan, from the point of view of the plan is:[6]

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

2.2. Managed care

Managed care rations the amount of health care a patient receives with minimal demand-side cost sharing, and thus without imposing much financial risk on enrollees.[7] Two approaches have been employed to model the rationing process.

[6] An alternative interpretation is that index i describes a group of people with the same $v_i(\boldsymbol{m}_i)$ function and $n_i(\boldsymbol{m}_i)$ is then the share of this group that joins the plan.

[7] Although health plans that are managed care may also use some demand-side cost sharing.

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 Pauly and Ramsey (1999). 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. Pauly and Ramsey (1999) show that some quantity setting is always part of the optimal combination of demand-side cost sharing and rationing. The plans of Glazer and McGuire (2000a) 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.[8]

An alternative approach to modeling managed care, used by Keeler et al. (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 sets just one shadow price.[9] Here, we adopt the shadow-price approach to managed care but allow for many services in order to study selection incentives.

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 $v_{is}(\cdot)$ 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 Fig. 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 or a physical capacity 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

[8] Risk adjustment can be viewed as a tax-subsidiary scheme used to equalize incentives to ration all services equally. This idea is developed in the general case of many services in Glazer and McGuire (2000b).

[9] 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.

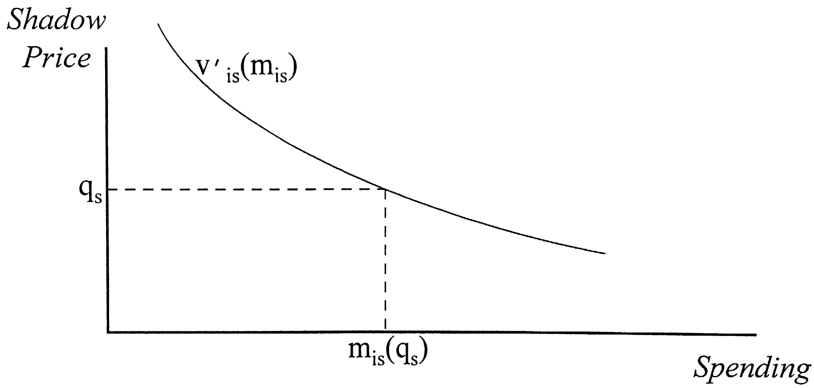

Fig. 1. Determination of spending on service s for individual i.

shadow price assumption is consistent with managed care rationing but with more care being received by patients who "need" it more.[10]

2.3. Profit and profit maximization

Let $\boldsymbol{q} = \{q_1, q_2, \ldots, q_s\}$ be a vector of shadow prices the plan chooses and $\boldsymbol{m}_i(\boldsymbol{q}) = \{m_{i1}(q_1), m_{i2}(q_2), \ldots, m_{is}(q_s)\}$ be the vector of spending individual i gets by joining the plan. Define $n_i(\boldsymbol{q}) \equiv n_i(\boldsymbol{m}_i(\boldsymbol{q}))$. Expected profit, $\pi(\boldsymbol{q})$, 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. Thus,

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

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 $\pi_i(\boldsymbol{q})$ to be the gain or loss on individual i:

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

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

$$\frac{\mathrm{d}\pi}{\mathrm{d}q_s} = \sum_i \left[\left(\frac{\mathrm{d}n_i}{\mathrm{d}q_s} \right) \pi_i - n_i m'_{is} \right] = 0. \tag{6}$$

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

[10] 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.

term is always positive, reflecting the savings the plan can achieve by rationing more stringently. The other term, $(\mathrm{d}n_i/\mathrm{d}q_s)\pi_i$, may be positive or negative for any individual. The term $\mathrm{d}n_i/\mathrm{d}q_s$ 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:

$$\frac{\mathrm{d}n_i}{\mathrm{d}q_s} = \frac{\mathrm{d}n_i}{\mathrm{d}v_{is}} \frac{\mathrm{d}v_{is}}{\mathrm{d}q_s}. \tag{7}$$

From (2), $\mathrm{d}n_i/\mathrm{d}v_{is}$ is simply Φ_i', and from (1) and (3), $\mathrm{d}v_{is}/\mathrm{d}q_s$ is $q_s m_{is}'$. Assuming that the elasticity of demand for service s is the same for all individuals for every q_s, 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 individuals 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 (2000a), 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:

$$\sum_i \left[\Phi_i' e_s m_{is} \pi_i - \frac{n_i e_s m_{is}}{q_s} \right] = 0. \tag{9}$$

Multiplying through by (q_s/e_s) and summing the terms separately,

$$q_s \sum_i \Phi_i' m_{is} \pi_i - \sum_i n_i m_{is} = 0,$$

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 (10) 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 (1995), 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. Eq. (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. It is only if a plan manipulates quality in more than one dimension of quality that risk adjustment of premiums paid to the plan has a role in countering selection incentives.[11]

2.4. 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 $\boldsymbol{q}$, 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

[11] Risk adjustment might also need to deal with individual-specific discrimination, such as, in the extreme, outright denial of enrollees. Glazer and McGuire (2000b) consider the questions of how best to design risk adjustment when quality discrimination and individual selection are both concerns.

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 $\boldsymbol{v}_t = \{v_{t1}(m_{t1}), v_{t2}(m_{t2}), \dots, v_{ts}(m_{ts})\}$ 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.

Each individual i is uncertain about his health state t, but has some prior distribution (beliefs) f_i over the set of possible states.[12] 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 modified model has three moves: first, the plan chooses its level of shadow prices $\boldsymbol{q} = (q_1, q_2, \dots, q_s)$, second, 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.

For a given shadow price q_s and a valuation function v_{ts}, the plan's expenditures on this individual on service s will be $m_{ts}(q_s)$, given by:

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

$$\text{Let } \boldsymbol{v}_t(\boldsymbol{q}) = \sum_s v_{ts}(m_{ts}(q_s))$$

The individual's expected utility is: $\mu + E_f[\boldsymbol{v}_t(\boldsymbol{q})]$.

Let $\bar{u}_t$ denote the individual's utility if his health state is t and he chooses the next best 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.[13] The plan, however, does not know the true value of μ, although it holds beliefs $\Phi(\mu)$ about its cumulative distribution.

[12] To use conventional terminology, individual i's prior beliefs, f_i, can be thought of as the individual's "type." As will be discussed in Section 3, one can make different assumptions about how an individual's prior beliefs are formed. Under some of these assumptions (e.g., beliefs are on the basis of "age" and "sex" only), several individuals may have the same prior beliefs, and hence be of the same "type." Thereafter, we will continue using the terminology "individual i", but one can think of this as "individual of type i."

[13] Although it simplifies the exposition, the assumption that the plan knows each individual's prior beliefs is much too strong for what we need. It is easy to show that all of our results will go through under a much weaker assumption: that the plan only knows the distribution of prior beliefs over the population, or, in other words, that the plan only knows the distribution of "types" in the population. This is a standard assumption in the asymmetric information literature.

A plan imposing shadow price $\boldsymbol{q}$ gauges the individual's likelihood of joining the plan as:

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

yielding an expected profit on the individual of:

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

The plan chooses each $\boldsymbol{q}$ to maximize expected profit. To find profit-maximizing values of $\boldsymbol{q}$, we differentiate the above with respect to $q_{s'}$:

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

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

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

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. Restoring the subscript i to Eq. (6$'$), summing Eq. (6$'$) over all i and setting it equal to zero, the profit maximizing q_s will be:

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

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

To investigate which shadow prices are set high relative to other shadow prices, we use Eq. (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. Eq. (10$'$) can now be used to write the ratio of two shadow prices, $\boldsymbol{q}$ and q'. Note that the Φ' term cancels out of this expression:

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

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.

2.5. 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

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

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

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

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

and assume that $n_i = n$, and $\Phi_i' = 1$ for all i.[14] Eq. (10′) can then be written as

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

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 $q_s = (n/r - \hat{M})$ for all s. Thus, in this case all shadow prices are the same and no distortion occurs. 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

[14] This is true with a uniform distribution.

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'.

As is also evident from (11), risk adjustment can counter the distortive forces discussed above. 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.

3. 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 are merely an example of how to implement our framework. In other words, our purpose here is to illustrate how to use presently available data to calculate a distortion index. 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. Our use of Medicaid data means that the population is not representative, but our findings are at least suggestive.

Recall from (11) that the profit maximizing shadow prices depend on the individuals' *expectations* regarding their future health needs. Therefore, the empirical building blocks for measuring shadow prices are the expected spending of individuals by service class and the correlation of expected spending across services under differing information assumptions. Our main strategy here 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 has been assessed over the past 15 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 Eq. (11) are computed from the predicted values generated from these estimated models.

3.1. 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. It is therefore important to highlight that the data we use consists largely of spending by poor women (90%); thus, calculated shadow prices may differ from those for other populations. 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, with a mean age of 32 years.

3.2. 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 nine 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.[15] We chose groups of conditions according to several criteria. 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, mental health care) and acute conditions (gastrointestinal, injuries, and birth-related). Treatments for some conditions are likely to be expensive, some much less so. 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.

3.3. Patterns of spending

Table 1 describes patterns of utilization and spending for the sample in 1993. The sixth and seventh columns of Table 1 indicate some of the key elements of the formula for shadow prices (11). The sixth column reports the intertemporal correlation between spending on each of our nine service categories and the sum of spending on all other services. None of correlations exceeds 0.20, with the

[15] Our grouping of services by ICD-9 codes is available from the authors.

Table 1
Use and cost in Michigan medicaid AFDC 1993

Service	Probability of any use	Expected spending given use (US$)	Expected costs (US$)	Percent of total costs	Correlation with all other costs	Correlation with own costs last year
Birth-related	0.167	3904	653	19.2	0.007	0.122
Cancer care	0.109	1159	126	3.7	0.155	0.127
Gastrointestinal	0.204	1186	242	7.1	0.167	0.166
Heart care	0.070	1542	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	1671	239	7.0	0.032	0.385
Musculoskeletal	0.306	683	209	6.1	0.115	0.215
Other/missing	0.926	1692	1567	45.9	0.313	0.288

exception of the "other" category. Correlation with spending in the previous year for each category is a measure of the persistence of spending, reported in the seventh column. Persistent spending is probably more predictable. Several of the illnesses 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 correlation.

3.4. Estimation of components of the ratio of shadow prices

3.4.1. 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).[16] In each case we adjusted the risk-adjusted premium 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 for all services.[17] The increase in premium was 50%.

3.4.2. 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 (1989) suggests that individuals know some of the information contained in measurable aspects of health status plus the time invariant-person specific component of the unobserved factors contributing to 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 et al. (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

[16] 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 the software provided by Randy Ellis of Boston University.

[17] One alternative would be to introduce some fixed cost assumption. If AC = MC and AC is close to average premium, there will be some services the plan will not wish to provide at all! To be willing to provide some of a service, a plan must make some expected profit on it. Another alternative would be to assume a plan is required to offer at least some minimum of every type of service.

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 all individuals predict they will spend the average for a person of their age and sex for each service category. Alternatively, we assume individuals can also 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 $\boldsymbol{q}$'s in profit maximization. In the simulations, we therefore equip individuals with some of the information in prior use, 40%, to illustrate 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 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 in 1993.

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

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

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

where i indexes the individual enrollee, $\boldsymbol{X}$ is a vector of individual characteristics (either age, sex, or age, sex, and prior use), $\boldsymbol{\beta}$ is a vector of coefficients to be estimated and ε is a random error term. Eq. (12) is a logit regression. Eq. (13) is a linear regression that estimates the impact of the $\boldsymbol{X}$'s 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.[18] The difficulties in retransforming the two-part model have been treated in detail by Manning (1998) and Mullahy

[18] We tested for heteroskedasticity logarithmic of the specification 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. The heteroskedasticity was attenuated, but still present, under the square root specification using the Breusch–Pagan test.

(1998).[19] 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, a "smearing factor" is taken from the error term of the 1991–1992 regressions. Because 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.

3.4.3. 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.

3.5. A welfare index

The welfare loss associated with a set of $\boldsymbol{q}$'s can be approximated by:

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

where Δq_s is the absolute value of the discrepancy between the $\boldsymbol{q}$ for service s and the second best $\boldsymbol{q}$, and Δm_s is the change in spending induced by the discrepancy in $\boldsymbol{q}$. For purposes of this analysis we define Δq_s as the difference between q_s and the weighted average $\boldsymbol{q}$ for all service types contained in Table 3. Thus, for each service s, we take the expenditure-weighted average $\boldsymbol{q}$ 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, except for mental health which we set at 0.5, based on Newhouse et al. (1997).

3.6. Results

We summarize the predictions of the 18 two-part models in Table 2 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

[19] Those papers show the sensitivity of expected spending estimates 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 predicted values of spending to the expected levels of spending consistent with the original distributions of spending (Duan et al., 1983).

Table 2
Correlations between actual and predicted spending with different information assumptions

Service	Model[a]	
	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

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

between actual and predicted spending is, however, relatively large at 0.21 (probably a result unique to a Medicaid sample). With prior use included, the correlation between predicted and actual spending improves markedly for most services.

The shadow prices implied by individuals' predictions and a risk adjustment policy are contained in Table 3. Two information assumptions are combined with three risk-adjustment policies to produce six sets of profit-maximizing shadow prices. The $\boldsymbol{q}$ for the "other" category is normalized to 1.00 in all cases, so each

Table 3
Shadow prices for three information assumptions and three risk adjustment systems

Service	Information assumption					
	Age, sex			Age, sex 40% of prior use		
	Risk adjuster			Risk adjuster		
	None	ADGs	HCCs	None	ADGs	HCCs
Birth-related	1.15	1.25	1.23	0.19	0.35	0.43
Cancer care	0.99	0.98	0.98	0.17	0.28	0.34
Gastrointestinal	0.99	0.99	0.99	0.18	0.29	0.36
Heart care	1.00	0.90	0.89	0.19	0.27	0.33
Hypertension	1.01	0.87	0.87	0.27	0.26	0.28
Injuries/poisonings	1.00	1.02	1.02	0.31	0.45	0.52
Mental health/substance abuse	0.99	0.98	0.98	3.73	0.67	0.76
Musculoskeletal	0.97	0.94	0.95	0.18	0.27	0.33
Other/missing	1.00	1.00	1.00	1.00	1.00	1.00
Weighted average of $\boldsymbol{q}$'s	1.03	1.04	1.04	0.82	0.67	0.70
Welfare loss (%)	0.6	1.1	1.0	9.7	3.9	3.6

Note: All shadow prices are relative to Other/Missing Category. Welfare loss is in terms of percent of total expenditures.

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. Risk adjustment using ADGs and HCCs magnifies the distortion in the cases of birth-related services, heart care and care for hypertension. The explanation is that people who anticipate using these services are paid for relatively generously in these two risk adjustment formulae.

The welfare loss measure at the bottom of the table corroborates the ***q*** results. When there is no risk adjustment and people forecast on age and sex, there is not much distortion, as indicated by the welfare loss as a percentage of spending. Risk adjustment exacerbates the welfare loss, though the magnitude is not high.

The second panel of three columns presents calculated ***q***'s, assuming individuals can predict spending based on 40% 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. Risk adjustment attenuates the distortions, moving all ***q***'s toward unity. Mental health and substance abuse services continue 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. Without risk adjustment, the welfare loss due to selection in the case when individuals know 40% of the information in prior use has risen to almost 10% of spending.[20] Risk adjustment appears to be quite effective, reducing the measured distortion to about 50% of its original magnitude.[21] A similar analysis could be conducted to examine how shadow prices change if we were to “carve-out” any of the service from the overall insurance contract. The obvious candidate for a carve-out, based on Table 3, is mental health and substance abuse.

[20] This is likely to be a conservative measure because of the way we construct elasticity.

[21] A next step in this analysis would be to find the “optimal risk adjustment.” Given a set of variables available for risk adjusting, Eq. (14) could be minimized with respect to the weights on the risk adjusters. It turns out it is possible to fully “solve” the optimal risk adjustment problem for the services if there are enough degrees of freedom in the variables available for risk adjustment (Glazer and McGuire, 2000b). This solution, or the minimization of Eq. (14), requires information on what plans believe individuals can predict.

As Table 3 shows, the calculations for shadow prices are sensitive to how much information individuals have in making their predictions. When we examined a scenario with individuals knowing as much as 50% of prior use, profit-maximizing the ***q***'s went "off the charts," signaling that incentives to over and underprovide are very strong.

4. 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.

From the practical standpoint of 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 empirically demonstrated. According to our preliminary analysis, if people know what they are sometimes commonly assumed to know (age, sex and prior spending), selection incentives would be very severe. Study of what individuals forecast is a key area of empirical research.

In our models if individuals know "too much," some services are not provided at all. We therefore analyze hypothetical cases in which individuals are not allowed to know "too much." Within this limitation, we illustrate how risk adjustment can be assessed. Two proposed risk adjustment systems have significant and similar effects in terms of cutting the magnitude of distortion incentives.

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