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Measuring Selection Incentives in Managed Care: Evidence from the Massachusetts State Employee Insurance Program

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Abstract

Health economists and policymakers have long recognized that capitation gives insurers incentive to manipulate their offerings to deter the sick and attract the healthy. The shadow-price approach to measuring such selection incentives was pioneered by Frank, Glazer and McGuire (2000). We extend their model to allow for partial capitation and nonfinancial concerns of insurers. We calculate three kinds of selection metrics using managed care medical and pharmacy spending data for fiscal years 2001 and 2002 from the Massachusetts state employee insurance program. Financial returns to risk selection are high, as indicated by all three selection indices as well as by the direct profits an insurer could earn if it could exclude unprofitable patients. Empirically, the financial temptation to distort service quality increases nonlinearly with supply-side cost sharing. The more an insurer directly values quality or patient benefit relative to profit, the less severe risk selection incentives become.

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Key words: risk selection; managed health care; shadow price; mixed payment

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1 Introduction

Health economists and policymakers have long recognized that capitation payment—or any payment featuring "supply-side cost sharing" (Ellis and McGuire 1990)—gives health plans and providers incentive to manipulate their offerings to deter the sick and attract the healthy. This behavior is variously known as "risk selection," "plan manipulation," "cream skimming," or "cherry picking" (Newhouse 1996; Cutler and Zeckhauser 1998 and 2000).[1] When health plans compete to avoid the sick rather than provide quality care, the most vulnerable patients may experience access problems. More generally, selection prevents individuals from being able to buy insurance against becoming a bad risk in the future (Newhouse 1996; Feldman and Dowd 2000). Selection thus can be considered both an efficiency and an equity problem.

To deter selection, employers and other purchasers frequently enforce open enrollment periods, proscribe pre-existing conditions clauses, and stipulate standard benefit packages. Yet health plans may engage in many subtle forms of risk selection. Examples include selective marketing, location of health facilities in profitable areas (see, e.g., Norton and Staiger 1994), staffing and infrastructure decisions, and distortion of the quality of specific services. We focus on the latter problem of service-specific quality distortions, pioneered by Frank, Glazer and McGuire (2000) and applied by Glazer and McGuire (2001, 2002a, 2002b), Cao and McGuire (2003) and Ellis and McGuire (2004).

In this paper, we use three different metrics of selection incentives to estimate empirically how a profit-maximizing insurer would want to distort service offerings to attract profitable enrollees. One method, proposed by Ellis and McGuire (2004), combines information about how predictable use of a service is, with whether prior spending on that service predicts future high costs (and thus greater insurance costs). The second method is the "shadow price" approach to managed care (Frank, Glazer and McGuire 2000; hereafter FGM), discussed momentarily. We propose a complementary third method which estimates the marginal net benefit to the insurer of deviating from a socially optimal level of care.

All three measures quantify the financial *temptation* to engage in risk selection; none measure the extent to which selection is actually taking place.[2] Research quantifying the extent to which insurers and providers

[1] Newhouse (1996) defines selection as "actions of economic agents on either side of the market to exploit unpriced risk heterogeneity and break pooling arrangements, with the result that some consumers may not obtain the insurance they desire" (p.1236).

[2] To emphasize this distinction, we include "incentives" in the title ("Measuring

respond to these financial incentives is an important complementary undertaking.

A health plan can discourage unprofitable customers from enrolling by stringently rationing the services valued by those customers. In the shadow-price approach to managed care, rationing is captured by the shadow price associated with each service.[3] By allocating a small budget to a given service or using other strategies (e.g., utilization review, financial incentives to providers, staffing limitations or other methods of making expensive services inconvenient), a health plan manager can increase the shadow price of access to that service. For example, a health plan may find it financially rewarding to limit access to mental health services (i.e., impose a high shadow price) but encourage access to preventive care (offer a low shadow price). Non-price mechanisms may include waiting time, geographic accessibility, and other dimensions of convenience. Which services are distorted depends on which consumers are unprofitable, determined by such factors as the level of the payment and the correlation of predicted spending between services.

In the original empirical application of the shadow-price approach, FGM demonstrate how profit-maximizing shadow prices can be estimated from individual-level health expenditure data, using Michigan Medicaid fee-for-service claims data for about 16,000 individuals spanning three years (1991-1993).

We extend FGM's theoretical model to allow for (a) nonfinancial concerns of providers (such as professional ethics and personal values); and (b) various forms of mixed or blended payments (partial capitation). Then we apply the method to more recent data for a larger and more representative employed population enrolled in managed care and indemnity plans. Our data include claims and managed care encounter data on both medical and pharmacy spending for fiscal years 2001 and 2002 (July 1, 2000 - June 31, 2002) from the Group Insurance Commission (GIC) of the Commonwealth of Massachusetts—one of the largest

selection incentives in managed care:...”), by contrast with FGM, “Measuring adverse selection in managed care.”

[3]The shadow price approach is entirely consistent with different intensity of service across patients.

Ma (2004) shows that an enrollee-group shadow price, rather than a service-specific shadow price, serves to maximize profits when allocating plan resources across services and enrollees. Although we acknowledge that this will be an interesting approach to explore empirically, we focus instead on service-specific shadow prices because they seem more consistent with empirical evidence on how providers serve heterogenous patients. For example, Glied and Zivin (2002) find visit duration to be constant across patients within a practice, and “physicians who treat mostly HMO patients appear to adopt a practice style that offers equivalent treatment intensity along most measurable dimensions” (p.353).

health care purchasers in New England. The selection indices we calculate thus represent the first application of these metrics to managed care data.

We find consistent results with all three measures of selection incentives: insurers have incentive to 'dump' enrollees with expensive heart conditions, diabetes or mental health and substance abuse problems (and to 'cream' enrollees with skin problems or conditions of the eyes, ears, nose and throat). Given previous evidence of risk segmentation in this population despite the GIC's many creative purchasing initiatives (Cutler and Zeckhauser 1998; Yu, Ellis and Ash 2001; Altman, Cutler, and Zeckhauser 2003), not surprisingly we find that risk adjustment considerably mitigates these selection incentives. The GIC's recent move towards all-encounter health-based risk adjustment among its plans is thus well warranted.

Economic theory suggests that mixed or blended payment – partial capitation – can be effective in combating risk selection (e.g., Ellis and McGuire 1990; Ma 1994; Newhouse 1996; Ma and McGuire 1997; Pauly 2000; Eggleston 2000; Newhouse 2002). Yet empirical evidence is limited regarding the effectiveness of mixed payment in reducing selection incentives. As far as we know, ours is the first empirical estimate of returns to risk selection over a full range of supply-side cost sharing. The results suggest a nonlinear relationship. Doubling the fraction of costs borne by plans or providers more than doubles the rewards to risk selection.

We also show theoretically and empirically that the more the plan directly cares about quality or patient benefit relative to profit, the less severe risk selection incentives become. Plan or provider "benevolence" (Chalkley and Malcomson 1998) can thus help to explain a somewhat perplexing finding in FGM. When patients know as much about their expected health spending as they are often assumed to know (e.g., what they spent last year), the plan's profit-maximizing shadow prices for FGM's sample went "off the charts" (FGM, p.851). Hence FGM calculate shadow prices assuming patients predict future use of services based on only 40% of prior use. A simple alternative explanation for why shadow prices would not actually go "off the charts" is provider benevolence or adherence to professional norms. Even when patients can predict their future spending needs quite accurately and an unconstrained profit-maximizing plan would have incentive for extreme quality distortions, the plan may be constrained from implementing such quality distortions by provider benevolence or the plan's own concern for reputation.

Finally, we supplement the analysis with a more conventional measure of selection incentives: the direct profits that an insurer could achieve by excluding unprofitable enrollees (see Shen and Ellis 2002). For the GIC managed care population, a risk-selecting health plan that successfully excludes unprofitable patients could increase profits, achieving a profit rate ranging from 14% to over 50%. Profits are generally higher, the more the plan knows relative to the payer. These results further underscore the strong financial temptation for insurers to invest in risk identification and selection.

The paper is organized as follows. We preface the empirical analysis with a discussion of the three selection indices, extending the theory of shadow prices to integrate non-pecuniary objectives and supply-side cost sharing. Section 3 describes the data and empirical strategy. Section 4 presents our empirical results. Section 5 concludes by summarizing our findings and suggesting the potential usefulness of the selection metrics for employers and other purchasers.

2 Theory of Shadow Prices and Managed Care

A health plan provides various health care services (e.g., prenatal care, treatment of heart attack patients, mental health services) indexed by j. Let m_j^i represent the spending on health service j provided to individual i, and $v_j^i\left(m_j^i\right)$ represent the increasing and concave ex ante utility individual i derives from that spending. Total service-related utility from joining the plan is $v^i\left(m^i\right) = \sum_j v_j^i\left(m_j^i\right)$. Following FGM, we also assume consumer valuation of a health plan includes some individual-specific factor μ_i such as convenience and premium differences. These individual-specific factors are distributed in the population according to the cumulative distribution $\Phi_i\left(\mu_i\right)$.

When choosing a health plan, each individual computes the expected utility from each plan available and chooses the plan that offers the highest utility. Given the spending levels in each plan, consumer i prefers a given health plan if and only if $v^i\left(m^i\right) + \mu_i > \overline{u}^i$, where $\overline{u}^i$ is the consumer's valuation of the next-preferred health plan. Plans must accept all applicants during an 'open enrollment period' enforced by the purchaser. The plan does not know each individual's μ_i, but it does know the cumulative distribution from which it is drawn. The plan considers the probability that individual i will enroll to be

$$\begin{aligned} n^i\left(m^i\right) &= prob\left(\mu_i > \overline{u}^i - v^i\left(m^i\right)\right) \\ &= 1 - \Phi_i\left(\overline{u}^i - v^i\left(m^i\right)\right). \end{aligned} \tag{1}$$

Demand increases in the spending generosity of the plan: $\frac{dn^i}{dm^i} = \Phi_i' \frac{dv^i}{dm^i} >$

0. Aware of this demand response to spending generosity, a profit-maximizing managed care plan can try to attract profitable patients with generous spending on services those enrollees value most, while simultaneously stinting on services disproportionately used by unprofitable patients.[4]

We follow the FGM model of managed care in using a shadow price approach, first used by Keeler, Carter and Newhouse (1998) and more recently applied in Glazer and McGuire (2002a, 2002b). The health plan sets a shadow price q_j for access to health service j such that "the patient must 'need' or benefit from services above a certain threshold in order to qualify for receipt of services" (FGM, p.836):

$$\frac{dv_j^i}{dm_j^i} = q_j. \tag{2}$$

A high shadow price represents stringent rationing. In the extreme (a shadow price approaching "infinity"), that service is simply not offered or covered at all. By contrast, a very low shadow price means little or no limitation on patient use of that service, i.e., full indulgence of moral hazard by insured consumers.

We can either think of the plan choosing the vector of service-specific shadow prices, q, directly, or that this is reflective of a more general framework in which there is a "division of responsibility between the 'management'... and 'clinicians"': "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" (FGM, p.836). See Eggleston and Yip (2004) for an explicit model of plan-physician contracting and physician choice of spending levels for each patient.

Health plans will respond to financial incentives when choosing shadow prices for various health services. Payment may be more generous for some services or patients than others. These financial incentives will shape the plan's desire to promote quality for specific services.

Assume payment includes two components. First, for each enrollee, the plan receives a fixed pre-payment (capitation) r^i. If capitation payments are risk adjusted, r^i will differ according to the risk adjusters (such as age, sex, and diagnoses of individual i) included in the risk adjustment formula. Risk adjustment can be a powerful tool to combat selection. Unfortunately, however, risk adjusters remain imperfect and

[4] We focus on the incentives facing a single representative health plan; analyzing market equilibria (when plans may face a prisoners' dilemma) is left to future research.

little used (see discussion in van de Ven and Ellis 2000 and Newhouse 2002). Our model focuses on the selection incentives remaining under any system with imperfect risk adjustment.

In addition to prepayment r, the plan receives reimbursement $(1 - s_j)\, m_j^i$ for each service j , with $s_j \leq 1$. Employers that contract for a fully insured product with no additional reimbursements, as for many HMOs, have $s_j = 0$ for all services. The health plan is at risk at point of service for the proportion of spending $s_j m_j^i$, and $s_j > 0$ denotes supply-side cost sharing (i.e., mixed payment). In practice, supply-side cost sharing does not often vary significantly across services (except sometimes for mental health and substance abuse in managed behavioral health carve-outs; see Frank and McGuire 2000). Usually the prepayment amount varies according to the degree of supply-side cost sharing, for example $r(s)$ with $\frac{dr}{ds} > 0$ and $r(s \leq 0) = 0$. Throughout our analysis we will assume that prepayment r is set to satisfy the plan's participation constraint, so that the plan wishes to attract positive enrollments from the payer,[5] and that $r(s)$ is set so that supply-side cost sharing is "budget neutral," i.e., the plan's expected profit is the same across all levels of supply-side cost sharing ($E\pi = r(s) - sm =$ constant).

This payment formulation can capture a wide range of linear plan reimbursement schemes. A fully capitated plan would receive a positive r^i per enrollee and be fully liable for costs of care, i.e., $s_j = 1$ for every service j. A mixed payment system features $0 < s < 1$. For example, McClellan (1997) finds that the cost-sharing features of the US Prospective Payment System correspond to $s \approx 0.5$. Pure cost reimbursement corresponds to $r = 0$ and $s = 0$. Fee-for-service payment with a positive profit margin arises when $s < 0$. For example, $s = -0.05$ would mean the plan is reimbursed $(1 - [-0.05])\, m_j^i = 1.05 m_j^i$, that is, receives a 5% profit margin above cost m_j^i.[6]

Given demand $n^i(q)$ and payment $r^i + \sum_j (1 - s_j)\, m_j^i(q)$ per enrollee,

[5] See Glazer and McGuire (2002b, Proposition 3) for a shadow-price model focusing on incentives for quality when plans and providers contract with multiple payers, in which a public payer such as Medicare must explicitly satisfy an plan participation constraint.

[6] Fee-for-service margins often differ by service, so that service-specific cost sharing and service-specific shadow prices extend readily to analysis of a detailed fee schedule with differing service-specific profit margins (see Eggleston and Yip 2004).

the health plan's expected net revenues $\pi(q)$ are

$$\begin{aligned}\pi(q) &= \sum_i n^i(q)\left[r^i + \sum_j (1-s_j)\, m_j^i(q) - \sum_j m_j^i(q)\right] \\ &= \sum_i n^i(q)\left[r^i - \sum_j s_j m_j^i(q)\right]. \end{aligned} \tag{3}$$

Assume $\pi(q)$ is strictly concave. Define $\pi^i(q)$ as the plan's gain or loss for individual i, $\pi^i(q) = r^i - \sum_j s_j m_j^i(q)$. Unprofitable enrollees are those for which $\pi^i(q) < 0$. Which enrollees are unprofitable will depend on several factors, including the level of the (possibly risk adjusted) payment, the enrollee's pattern of service utilization, and the degree of supply-side cost sharing on the services used by the enrollee.

We extend FGM's theory by incorporating benevolence or professional ethics into the health plan's objective function. A health plan may have goals beyond, or that moderate, profit maximization. Some health plans are nonprofit, with an explicit commitment to a mission other than maximizing returns for stockholders. Even ostensibly profit-maximizing plans may wish to establish a reputation for high quality and no discrimination against vulnerable patients. Clinicians may care directly about the patients they serve, and only agree to contract with plans that do not constrain their clinical decisionmaking too stringently, thus indirectly constraining plan behavior.

Let the plan's degree of fidelity to patient interests be denoted by α. The health plan then maximizes an objective function that includes not only expected profits but also α weight on patient valuation of treatment benefits:

$$\begin{aligned} V &= \sum_i n^i(q)\left[r^i - \sum_j s_j m_j^i(q) + \alpha \sum_j v_j^i\left(m_j^i(q)\right)\right] \\ &= \sum_i n^i(q)\left[\pi^i + \alpha v^i\right] \end{aligned} \tag{4}$$

FGM analyze the case of a pure profit maximizer ($\alpha = 0$) paid on a capitation basis ($s = 1$), in which case V reduces to $\pi(q(s=1))$.

The plan chooses the shadow price for each service j to maximize V (4):

$$\frac{dV}{dq_j} = \sum_i \left(\frac{dn^i(q)}{dq_j}\left[\pi^i + \alpha v^i\right] + n^i(q)\left[\frac{d\pi^i}{dq_j} + \alpha \frac{dv^i}{dq_j}\right]\right) = 0, \text{ or}$$

$$\sum_i \left(-n^i s_j \frac{dm_j^i}{dq_j}\right) = \sum_i \left(-\frac{dn^i}{dq_j}\left[\pi^i + \alpha v^i\right] - n^i \alpha \frac{dv^i}{dq_j}\right) \tag{5}$$

This first order condition describes the trade-off a plan makes in setting the shadow price for each service. The plan's marginal benefit from raising the shadow price is less spending per enrollee, $-n^i s_j \frac{dm_j^i}{dq_j} > 0$. Consider a pure profit-maximizing plan, $\alpha = 0$. The plan's marginal cost of raising q_j is discouraging profitable patients from joining the plan ($-\frac{dn^i}{dq_j}\pi^i > 0$ if $\pi^i > 0$). The higher the profit margin per enrollee, the less attractive risk selection becomes. As FGM note, "the idea behind competition among managed care plans is that ... the plan by rationing too tightly will lose profitable customers – to balance the plan's incentive to reduce services to the existing enrollees" (p.838). Agency on behalf of patients discourages stinting by adding additional terms to the marginal cost of raising q_j: $-\alpha \left\{\frac{dn^i}{dq_j} v + n^i \frac{dv^i}{dq_j}\right\} > 0$.

If the payment system does not include any supply-side cost sharing ($s \leq 0$), the left-hand side of (5) is zero or negative, and plans will not want to restrict access to services. This is consistent with a low threshold for use, and wasteful over-use, under cost reimbursement or fee-for-service ($q_j^* = 0$).

The condition (5) thus defines the profit-maximizing shadow price as the shadow price that balances the marginal benefit and marginal cost of increasing q_j, or, equivalently, causes the net marginal benefit of raising q_j to equal zero:

$$\underbrace{\sum_i \left(-n^i s_j \frac{dm_j^i}{dq_j}\right)}_{\text{Marginal Benefit to Plan}} - \underbrace{\sum_i \left(-\frac{dn^i}{dq_j}\left[\pi^i + \alpha v^i\right] - n^i \alpha \frac{dv^i}{dq_j}\right)}_{\text{Marginal Cost to Plan}} = 0 \tag{6}$$

Clearly, the profit- or utility-maximizing shadow price can exceed or fall short of the socially optimal value, $q^{**} = 1$, which equates patient marginal treatment benefit with social marginal cost for each service:

$$q^{**} = \arg\max\left[v\left(m\left(q\right)\right) - m\left(q\right)\right] = 1 \tag{7}$$

The benefits of some degree of supply-side cost sharing are well established in the theoretical literature (Ellis and McGuire 1990; Ma 1994; Newhouse 1996; Ma and McGuire 1997; Eggleston 2000; van Barneveld, Lamers, van Vliet, and van de Ven 2001). The argument for some supply-side cost sharing holds for both profit-maximizing and altruistic plans and providers. Indeed, genuine concern for patient welfare reinforces the argument, because providers that act as good agents for fully insured consumers will indulge patient moral hazard, contributing to overspending under cost reimbursement. Supply-side cost sharing helps to control over-spending, but gives plans incentive to control spending differentially by service. Stinting disproportionately on the services attractive to expensive consumers discourages their enrollment and hence achieves risk selection. Similarly, overspending on services valuable to profitable consumers (such as discounts on health club membership or yoga classes) lures them to enroll. Call such selection-motivated disparities in spending or shadow prices "quality-distortion selection." Higher supply-side cost sharing induces more quality-distortion selection.

Different degrees of supply-side cost sharing for different services might improve incentives relative to uniform payment. However, varying supply-side cost sharing by service may be too administratively cumbersome to be practical, even if analysts could pinpoint optimal service-specific cost sharing. Nevertheless, employers and other purchasers can use information about "vulnerable services" in applying a whole gamut of purchasing strategies, including quality monitoring. A purchaser that discovers hypertension treatment and behavioral health services to be extremely vulnerable to selection-motivated quality distortions, for example, could target quality monitoring time and effort on those particular services. Perhaps a payment adjustment, such as a carve-out for behavioral health, would be suitable; but clearly this will not be practical for all "high risk" services. Instead, the purchaser can use quality monitoring and payment refinement as complementary purchasing strategies.

2.1 Empirically Estimating Selection Incentives

Ellis and McGuire (2004) propose a selection index based on the first-order condition (6). They focus on two elements of predicted profitability of offering a service: how predictable use of the service is, and how predictive spending is of overall costs. Insurers have incentive to ration services that are predictable and associated with high total cost. Let $\widehat{m}_j^i$ denote consumer i's predicted spending on service j. Their proposed selection index for service j is the product of two terms: the coefficient of variation in predicted service spending $\widehat{m}_j$ (i.e., the standard deviation of $\widehat{m}_j$ divided by its mean), multiplied by the contemporaneous Pearson's correlation between $\widehat{m}_j$ and total actual spending.

For the second, shadow-price approach to measuring selection incentives, FGM show that for the special case of a pure profit maximizer paid on a capitation basis ($\alpha = 0$; $s = 1$),

$$q_j = \frac{\sum_i n^i m_j^i}{\sum_i \Phi_i' m_j^i \pi^i}. \tag{8}$$

Generalizing to include supply-side cost sharing and nonpecuniary objectives, we find that

$$q_j = \frac{s_j \sum_i n^i m_j^i}{\sum_i \left(\Phi_i' m_j^i \left[\pi^i + \alpha v^i\right] + \alpha n^i m_j^i\right)}. \tag{9}$$

For a profit-maximizing plan, $\alpha = 0$ and

$$q_j = \frac{s_j \sum_i n^i m_j^i}{\sum_i \Phi_i' m_j^i \left[r^i - \sum_j s_j m_j^i\right]}. \tag{10}$$

A straightforward extension of the FGM generalization to uncertainty (FGM pp.839-843) yields the following empirically implementable shadow price index:

$$q_j = \frac{s_j n \widehat{m}_j}{r\widehat{m}_j + \widehat{\rho}_{rj}\widehat{\sigma}_j\widehat{\sigma}_r - \left(s_j\widehat{\sigma}_j^2 + \sum\limits_{j' \neq j} s_{j'}\widehat{\rho}_{j,j'}\widehat{\sigma}_j\widehat{\sigma}_{j'} + \widehat{m}_j \overline{s}\widehat{M}\right)}, \tag{11}$$

where $\widehat{m}_j = \dfrac{\sum\limits_i \widehat{m}_j^i}{N}; \qquad r = \dfrac{\sum\limits_i r^i}{N}$

$$\widehat{\sigma}_j = \sqrt{\frac{\sum\limits_i \left(\widehat{m}_j^i - \widehat{m}_j\right)^2}{N}}; \qquad \widehat{\sigma}_r = \sqrt{\frac{\sum\limits_i \left(r^i - r\right)^2}{N}}$$

$$\widehat{\rho}_{j,j'} = \frac{\sum\limits_i \left(\widehat{m}_j^i - \widehat{m}_j\right)\left(\widehat{m}_{j'}^i - \widehat{m}_{j'}\right)}{N\widehat{\sigma}_j\widehat{\sigma}_{j'}}; \widehat{\rho}_{rj} = \frac{\sum\limits_i \left(r^i - r\right)\left(\widehat{m}_j^i - \widehat{m}_j\right)}{N\widehat{\sigma}_j\widehat{\sigma}_r}$$

$$\overline{s} \equiv \frac{\sum\limits_j s_j \widehat{m}_j}{\sum\limits_j \widehat{m}_j}; \qquad \widehat{M} = \sum_j \widehat{m}_j$$

In (11), $\widehat{m}_j$ is the average of all consumers' predicted spending on service j; r is the average capitation payment, where the capitation payment is adjusted upward from that predicted by the given risk adjustment method so that all patients are profitable (following FGM, $r^i = 1.5 r_{HCC}^i$); $\widehat{\sigma}_j$ is the standard deviation of consumers' expected spending on service j; $\widehat{\sigma}_r$ is the standard deviation of risk-adjusted capitation payments; $\widehat{\rho}_{j,j'}$ is the correlation coefficient between predicted spending on service j and predicted spending on service j'; $\widehat{\rho}_{rj}$ is the correlation coefficient between risk-adjusted capitation payments and predicted spending on service j'; $\overline{s}$ is the weighted average degree of supply-side cost sharing, weighted by average predicted spending for each service j; and $\widehat{M}$ is the average total predicted spending for consumers, i.e., the capitation payment that would make the plan just break even if every enrollee had average predicted spending.

Predicted spending $\widehat{m}_j$ depends on how much information individuals have and use when choosing health plans. FGM compare predicted spending under two information assumptions: based only on age and sex, and based on age and sex plus some of the information embodied in prior use of health services (40%). We estimate predicted spending for these information assumptions plus all of the information in prior use (100% prior use; see Table 2). We follow FGM in reporting shadow prices relative to the shadow price for "all other services."

We propose a third measure of selection incentives. For some policy and analytic questions, it can also be useful to think of the empirical formula for service-specific shadow prices (11) as allowing empirical estimation of the net marginal benefit of risk selection. As noted above in (6), profit-maximizing shadow prices are those that set the marginal benefit of raising shadow prices equal to the marginal cost of doing so (i.e., losing some profitable enrollees). Suppose instead that plans had to set shadow prices at the socially optimal value of 1. When $q_j = 1$, the marginal benefit of risk selection would outweigh its marginal cost, at least for some services j. One can estimate the marginal benefit of risk selection less its marginal cost, or the *net marginal benefit of risk selection (NetMB)*, assuming $q = 1$ and $n = 1$, as follows:

$$NetMB = \sum_j \left(\frac{\widehat{m}_j}{M}\right) Max\left[NetMB_j, 0\right] \tag{12}$$

where $NetMB_j = \underbrace{\left[s_j \widehat{m}_j\right]}_{\text{Marginal Benefit}} -$

$$\underbrace{\left[r\widehat{m}_j + \widehat{\rho}_{rj}\widehat{\sigma}_j\sigma_r - \left(s_j\widehat{\sigma}_j^2 + \sum_{j'\neq j} s_{j'}\widehat{\rho}_{j,j'}\widehat{\sigma}_j\widehat{\sigma}_{j'} + \widehat{m}_j\overline{s}\widehat{M}\right)\right]}_{\text{Marginal Cost}}$$

This captures the financial temptation or reward to health plans for deviating from socially-optimal quality for specific services. The plan has financial incentive to risk select when the net marginal benefit of doing so is positive. When the cost of service distortions—in terms of forgone enrollment (or damaged reputation)—outweighs the benefit, the net marginal benefit is negative, and the plan will no longer have an incentive to risk select. Hence the total net marginal benefit of risk selection aggregates across only those services for which the net marginal benefit of selection is positive. We define $NetMB$ as the weighted average of the incentive to risk select for specific services, where the weights are the share of predicted spending on each service ($\frac{\widehat{m}_j}{\widehat{M}}$).

We use this measure to examine empirically how selection incentives differ across different degrees of supply-side cost sharing–with s ranging between 0 (cost reimbursement) and 1 (fully prospective payment or capitation).[7] We assume that the plan's expected profit is constant regardless of the degree of supply-side cost sharing. Specifically, expected net revenue per patient is equal to half the average capitation payment: $E\pi = r(\overline{s}) - \overline{s}\widehat{M}, = 0.5\widehat{M}$, so that $r(\overline{s}) = (0.5 + \overline{s})\,\widehat{M}$.[8]

Empirically estimating the net marginal benefit of selection also allows policymakers to quantify how much provider altruism, or caring for patients, helps to mitigate selection. Agency on behalf of patients increases the value of the shadow price denominator by a positive term, hence decreasing the shadow price. (In the limit, a provider who is a "super-agent" for his or her patients will not wish to restrict access to any services, and the resulting shadow prices will all be 0.) We proxy a patient's value for the plan, v^i, with average total predicted spending, $\widehat{M}$, as arguably a plausible lower bound. The additional agency term in the denominator of shadow price q_j can then be expressed as $\alpha\widehat{m}_j\left(\widehat{M} + n\right) \approx \alpha\widehat{m}_j\widehat{M}$. We calculate shadow prices and the net benefit of selection for various degrees of provider benevolence by adding the term $\alpha\widehat{m}_j\widehat{M}$ to the denominator of (11) or to the marginal cost term of (12).

3 Data and Empirical Strategy

The shadow price approach has been developed to be applied to managed care, yet it has not yet been so applied; we do so. Our data

[7]We use this measure because the shadow prices themselves do not well capture the change in incentives as s or α change from 0 to 1 (or greater for α). This is because the "raw" shadow prices (i.e., not in ratios to "other services") "switch over" to negative values at differing rates as s decreases and/or α increases, causing the ratio of shadow prices to fluctuate seemingly wildly. The net marginal benefit of selection metric avoids this problem by using the difference, rather than the ratio, of the empirically estimated marginal benefit and marginal cost of selection. It is an intermediate metric between shadow prices and the Ellis and McGuire (2004) selection index.

[8]In the case of risk adjustment, both the average capitation payment and its standard deviation vary with s.

include claims and managed care encounter data–diagnoses and both medical and pharmacy spending–from the Group Insurance Commission (GIC) of the Commonwealth of Massachusetts, one of the largest health care purchasers in New England. The GIC offers beneficiaries a choice of an indemnity plan, a Preferred Provider Organization, and several Health Maintenance Organizations (HMOs). We focus on those enrolled in HMOs, but also compare results to those for enrollees in the indemnity plan.[9] For more detail on the GIC and previous evidence of risk selection among their plans, see Cutler and Zeckhauser (1998), Altman, Cutler and Zeckhauser (1998, 2003), and Yu, Ellis and Ash (2001).

We linked eligibility and medical claims for two fiscal years, from July 1, 2000 to June 30, 2002. The GIC holds open enrollment in June of each year. The data thus cover two years of enrollment. Throughout the analysis, "year 1" refers to fiscal year 2001 (July 2000 - June 2001), and "year 2" refers to fiscal year 2002 (July 2001 - June 2002).

The data extract that we obtained through Medstat, which manages the data for the GIC, includes a variable coded as managed care, indemnity or PPO. For the "HMO enrollees" sub-sample (65,615 enrollees), we included all continuously enrolled,[10] non-elderly adults (age 18-64) who were coded as being in a managed care plan in both years. Thus, we pool the encounter data across all the HMOs offered by the GIC. We also look separately as the sub-sample of non-elderly adults continuously enrolled in the indemnity plan (86,365).[11]

The spending variable represents total covered charges, including patient out-of-pocket payments.[12] We examined selection incentives with

[9]The shadow prices estimated from the GIC HMO encounter data reveal the selection incentives that the HMOs face. Shadow prices for the enrollees in the indemnity plan (which the GIC self-insures), in contrast, predict selection incentives for the hypothetical yet policy-relevant case of switching those enrollees into managed care. These characterize incentives that would appear if the GIC removed the non-managed care plan options for those beneficiaries (e.g., forced them into HMOs). They also give information about how current managed care plans may try to discourage those currently in the indemnity plan from switching into an HMO. The indemnity plan shadow prices are most relevant for comparing results with those of FGM, who used non-managed-care data.

[10]Eligibility information was coded as a dummy variable for each quarter. We counted as continuously enrolled anyone who was eligible for all eight quarters of the data.

[11]By including enrollees only under age 65, we avoid the complications of including the 41% of indemnity-plan enrollees who are on Medicare. Only 412 indemnity plan enrollees (about 1%) are under age 65 and enrolled in Medicare. All GIC beneficiaries who are on Medicare enroll in the indemnity plan.

[12]The total charge allowed is the amount of submitted charges eligible for payment for all claims. It is the amount eligible after applying pricing guidelines, but before

spending defined to include charges for medical plus pharmacy spending. Unfortunately the pharmacy data did not include diagnoses that would allow allocating drug spending to specific service categories. Therefore we allocated pharmacy spending to service categories in proportion to medical spending in the same year.

To define categories of medical services, we followed closely the methodology of FGM: a mixture of chronic and acute conditions, with a sizeable percentage of enrollees (no fewer than 10%) using each service in each year. The categories replicate the strategy employed by FGM but not their exact service categories, since not all are as appropriate for our sample as for their Medicaid sample. (For example, birth services were a large category for FGM's AFDC-eligible Medicaid sample but not for our sample).

Descriptive statistics on the percentage of enrollees who used each of our 11 defined services and their costs are shown in Table 1. They show how the managed care and indemnity plan enrollee populations differ. Indemnity enrollees have a higher probability of use for almost every service. Risk assessment using Diagnostic Cost Group estimated risk score of the population also underscores how much healthier HMO enrollees are on average. The HMO sample has an average risk score of 1.303 using all-encounter data; by contrast, indemnity plan enrollees have an average risk score of 1.915.

Mental health and substance abuse spending is highly predictable with information on prior use, as revealed by the last column of Table 1, correlation with own costs last year. However, for both the managed care and indemnity plan enrollees, spending on mental health and substance abuse has one of the lowest correlations with all other costs, suggesting that this service may not be highly predictive of high-cost individuals. Note that the mental health and substance abuse component of the indemnity plan is carved out to a managed behavioral health provider; consistent with this, utilization of this service is similar across the HMO and indemnity plan enrollees.

deducting third party, copayment, coinsurance, or deductible amounts.

Table 1a. Patterns of spending, GIC managed care, Estimation sample (N=32,153), Fiscal year 2002 (July 2001 – June 2002)

Service	Probability of Any Use	Expected Cost Given Use ($)	Expected Costs ($)	Percent of Total Costs	Correlation with all other costs	Correlation with own costs last year
Injuries	17.1	846.01	144.51	5.5	0.068	0.280
Cancer and screening	19.6	1520.02	297.36	11.4	0.104	0.310
Diabetes	23.6	507.73	119.73	4.6	0.115	0.698
Digestive conditions	14.3	1296.47	185.72	7.1	0.097	0.330
Musculoskeletal conditions	30.2	894.04	270.00	10.4	0.116	0.283
Mental Health/ Substance Abuse	12.8	1081.71	138.31	5.3	0.031	0.538
Cardiac care	18.6	1287.61	240.08	9.2	0.132	0.156
Eye, Ears, Nose, and Throat	33.2	437.48	145.14	5.6	0.104	0.336
Urogenital conditions	22.2	845.25	187.86	7.2	0.071	0.486
Skin conditions	17.4	355.17	62.00	2.3	0.095	0.238
Other conditions	74.6	1076.39	802.71	30.8	0.262	0.281

Table 1b. Patterns of spending, GIC Indemnity Plan, Estimation sample, Fiscal year 2002 (July 2001 – June 2002)

Service	Probability of Any Use	Expected Cost Given Use ($)	Expected Costs ($)	Percent of Total Costs	Correlation with all other costs	Correlation with own costs last year
Injuries	18.9	1645.11	310.50	6.0	0.153	0.097
Cancer and screening	29.3	2420.21	709.15	13.7	0.074	0.359
Diabetes	34.7	775.21	268.78	5.2	0.086	0.217
Digestive conditions	19.7	1880.48	371.03	7.1	0.044	0.077
Musculoskeletal conditions	40.4	1660.89	671.61	12.9	0.051	0.323
Mental Health/ Substance Abuse	12.5	1655.00	206.65	4.0	0.037	0.522
Cardiac care	30.9	2339.50	723.00	13.9	0.152	0.167
Eye, Ears, Nose, and Throat	39.3	689.88	271.29	5.2	0.044	0.252
Urogenital conditions	27.9	1470.36	410.83	7.9	0.056	0.487
Skin conditions	24.5	529.09	129.86	2.5	0.080	0.075
Other conditions	73.2	1504.72	1102.19	21.2	0.192	0.313

Calculating shadow prices requires estimating individual predicted expenditures for various information assumptions about how enrollees choose plans. Potential enrollees may not have full information about the detailed service offerings of each plan, and they might know their own precise risk level or how to predict their future use for all services. Operationally, enrollee informational assumptions correspond to the covariates included in the expenditure prediction regression model (e.g., age, gender, prior expenditure). "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....In the simulations, we equip individuals with some of the information in prior use, 40%, to illustrate the impact of more information" (FGM 2000, p.847). For comparability with FGM's results, we report results for 40% as well as 100% prior use.

Since our data include only two years of spending rather than the three years that FGM use, we employ a split-sample methodology to calculate predicted spending in the second year. That is, first we divide the sample randomly into equal estimation and prediction sub-samples. Second, we regress year 2 spending on age and sex (represented by six age-gender "cells" of ages 18-40, 41-50, and 51-64) and year 1 spending using the estimation sub-sample. Third, we use the prediction sub-sample to predict spending in year 2 based the estimated regression coefficients and enrollees' age, sex and year 1 spending. Predicted spending for each service uses the full array of 11 services' prior use as explanatory variables. We estimate spending with two-part models, like FGM. (Results with ordinary least squares were broadly similar.)

Table 2 shows the correlations between actual and predicted spending with our different information assumptions. As the information used to predict spending increases, correlations increase, with the largest jump between age-sex-only and age-sex and some prior use. Mental health and substance abuse, musculoskeletal conditions and diabetes are the most predictable with prior use; injuries are among the least predictable services.

To illustrate the impact of diagnosis-based risk adjustment on selection, we calculate shadow prices with and without risk adjusting premiums based on the Diagnostic Cost Group / Hierarchical Condition Category (DCG/HCC) model (Pope, Ellis, Ash, et al. 2000).

Table 2a. Correlations between actual and predicted spending with different information assumptions GIC managed care (HMO enrollees), 2PM predicted spending

Service	Model		
	Age, Sex	Age, Sex, 40% Prior Use	Age, Sex, 100% Prior Use
Injuries	0.00	0.18	0.22
Cancer and screening	0.02	0.21	0.22
Diabetes	0.05	0.44	0.44
Digestive conditions	0.03	0.27	0.28
Musculoskeletal conditions	0.07	0.31	0.32
Mental Health/ Substance Abuse	0.02	0.53	0.53
Cardiac care	0.10	0.23	0.23
Eye, Ears, Nose, and Throat	0.02	0.27	0.27
Urogenital conditions	0.05	0.31	0.34
Skin conditions	0.02	0.29	0.30
Other conditions	0.08	0.20	0.25

Table 2b. Correlations between actual and predicted spending with different information assumptions
GIC indemnity plan enrollees, 2PM predicted spending

Service	Model		
	Age, Sex	Age, Sex, 40% Prior Use	Age, Sex, 100% Prior Use
Injuries	0.01	0.12	0.12
Cancer and screening	0.04	0.30	0.31
Diabetes	0.06	0.27	0.28
Digestive conditions	0.02	0.09	0.09
Musculoskeletal conditions	0.05	0.34	0.34
Mental Health/ Substance Abuse	0.03	0.52	0.52
Cardiac care	0.08	0.21	0.21
Eye, Ears, Nose, and Throat	0.03	0.31	0.31
Urogenital conditions	0.01	0.24	0.27
Skin conditions	0.01	0.12	0.12
Other conditions	0.03	0.18	0.21

4 Empirical Results

We find consistent results using all three measures of selection incentives. Estimation of the Ellis-McGuire Selection Index (Table 3, Figure 1) reveals that the most at-risk services are cardiac, diabetes and cancer care for the HMO population, and cardiac, mental health/substance abuse, cancer and diabetes care for the FFS population. The plan has least incentive to distort services for injuries and conditions of the eyes, ears, nose and throat. As the descriptive statistics suggested, the coefficient of variation for mental health and substance abuse is among the highest, but spending on this service is not highly correlated with total spending, so the overall selection index is moderate, especially for the HMO population. The average selection index is low when only an enrollee's age and sex are used to predict spending; incentive for selection distortions increases significantly when prior use of services is also used to predict spending.

The empirically estimated shadow prices for GIC managed care and indemnity plan enrollees are shown in Table 4 for three information assumptions and two risk adjustment systems. The incentive to risk select decreases with risk adjustment (for any given information assumption) and increases with the information (i.e., percentage of prior use) that enrollees use when choosing among plans. Note the greater dispersion of shadow prices when enrollees have "full information"—that is, base health plan choice on all the information embedded in their prior utilization of services.

The service with the highest shadow prices—indicating that the plan has financial incentive to stint—is cardiac care (for both the managed care and indemnity plan samples). Other services with shadow prices greater than 1 include diabetes and mental health and substance abuse. Figure 2 illustrates the dispersion of shadow prices by service category, and how they change with risk adjustment, assuming enrollees are equipped with the information embodied in 40% prior use. All the shadow prices tend to move toward the weighted average (generally closer to 1) when premiums are risk adjusted. For example, risk adjustment dramatically reduces the shadow price for cardiac care.

The value of risk adjustment in mitigating selection incentives is also manifest in the last row of Table 4: To estimate shadow prices, the analyst usually needs to multiply premiums by some factor so that all services are profitable for a plan to supply (i.e., no estimated shadow prices should be negative). FGM multiplied premiums by 50%. We find that premiums must be multiplied by up to a factor of 14 (for the indemnity plan assuming 100% prior use). With risk adjustment, premiums need only be multiplied by a much smaller multiple in order to make all shadow prices positive.

Quality problems can arise from overuse as well as underuse. A shadow price significantly below the weighted average indicates that the plan has financial incentive to “cream” enrollees by generously providing that service. For the HMO enrollee sample, such services include treatment for skin or urogenital conditions. Risk adjustment only partially “corrects” these creaming incentives.

The new metric proposed here, the net marginal benefit of selection, shows the same pattern of incentives to distort services (see Figure 2): cardiac care shows the highest benefit to the plan from rationing; “other” services are also high; and there is no net marginal benefit to rationing care for injuries. For neither this selection index nor that proposed by Ellis and McGuire (2004) does the analyst need to multiply premiums by an arbitrary amount. An additional advantage of the net marginal benefit of selection index is in empirically examining the impact of mixed payment and provider ‘benevolence,’ to which we now turn.

Table 3. Ellis-McGuire Selection Index, GIC Indemnity and HMO Enrollees

Name	Indemnity CV	Indemnity corr(m^,M)	Indemnity Selection Index	HMO CV	HMO corr(m^,M)	HMO Selection Index
Predicting spending with enrollee's age and sex only						
Other conditions	0.614	0.025	0.016	0.645	0.058	0.037
Cancer and screening	0.613	0.060	0.037	0.649	0.066	0.043
Diabetes	0.598	0.085	0.051	0.784	0.075	0.059
Digestive	0.276	0.074	0.020	0.310	0.035	0.011
Musculoskeletal	0.618	0.057	0.035	0.604	0.053	0.032
Mental Health/Substance Abuse	0.367	-0.080	-0.029	0.163	-0.089	-0.014
Cardiac	0.880	0.069	0.061	1.018	0.069	0.071
Eye, Ears, Nose, Throat	0.302	0.054	0.016	0.162	0.043	0.007
Urogenital	0.582	0.006	0.003	0.642	0.031	0.020
Skin	0.180	0.087	0.016	0.128	0.054	0.007
Injury	0.222	-0.054	-0.012	0.369	-0.069	-0.026
Average	0.477	0.035	0.019	0.497	0.030	0.022
Predicting spending with age, sex, and 40% prior use						
Other conditions	0.858	0.195	0.167	0.696	0.182	0.126
Cancer and screening	1.948	0.219	0.427	1.718	0.217	0.372
Diabetes	2.222	0.199	0.442	2.895	0.196	0.568
Digestive	1.100	0.226	0.248	1.045	0.210	0.219
Musculoskeletal	1.739	0.196	0.340	1.375	0.200	0.275
Mental Health/Substance Abuse	4.703	0.123	0.577	3.499	0.098	0.342
Cardiac	3.507	0.177	0.620	4.410	0.171	0.755
Eye, Ears, Nose, Throat	1.094	0.168	0.183	0.676	0.168	0.113
Urogenital	1.147	0.136	0.156	1.169	0.170	0.199
Skin	1.116	0.163	0.182	0.504	0.253	0.128
Injury	0.886	0.172	0.152	0.581	0.127	0.074
Average	1.847	0.179	0.318	1.688	0.181	0.288
Predicting spending with age, sex, and 100% prior use						
Other conditions	1.359	0.237	0.321	0.981	0.250	0.245
Cancer and screening	2.854	0.220	0.627	2.967	0.218	0.647
Diabetes	2.985	0.196	0.585	3.949	0.194	0.764
Digestive	2.150	0.222	0.477	2.342	0.210	0.493
Musculoskeletal	2.575	0.196	0.505	2.350	0.204	0.479
Mental Health/Substance Abuse	5.255	0.123	0.648	4.442	0.099	0.438
Cardiac	4.067	0.176	0.715	5.469	0.170	0.929
Eye, Ears, Nose, Throat	1.856	0.167	0.309	1.422	0.167	0.237
Urogenital	2.446	0.154	0.377	2.333	0.189	0.440
Skin	2.142	0.159	0.341	1.415	0.251	0.355
Injury	1.689	0.181	0.306	1.169	0.181	0.212
Average	2.671	0.185	0.474	2.622	0.194	0.476

CV = coefficient of variation of service-specific predicted spending (standard deviation/mean);
corr(m^,M) = correlation between predicted spending on that service and total spending.

Figure 1. Ellis-McGuire Selection Index
(GIC HMO and Indemnity Plan enrollees, 100% prior use, 2PM)

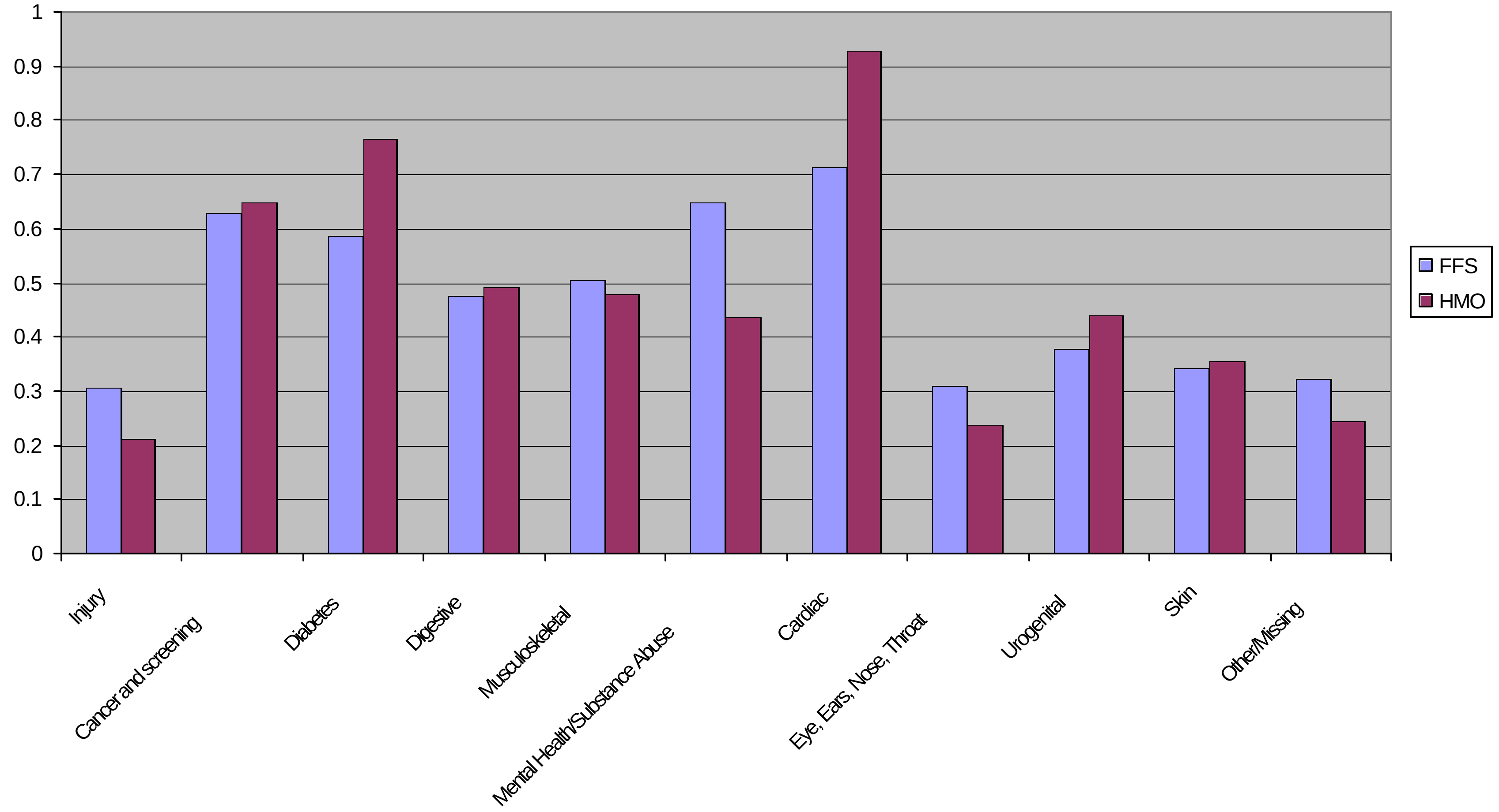
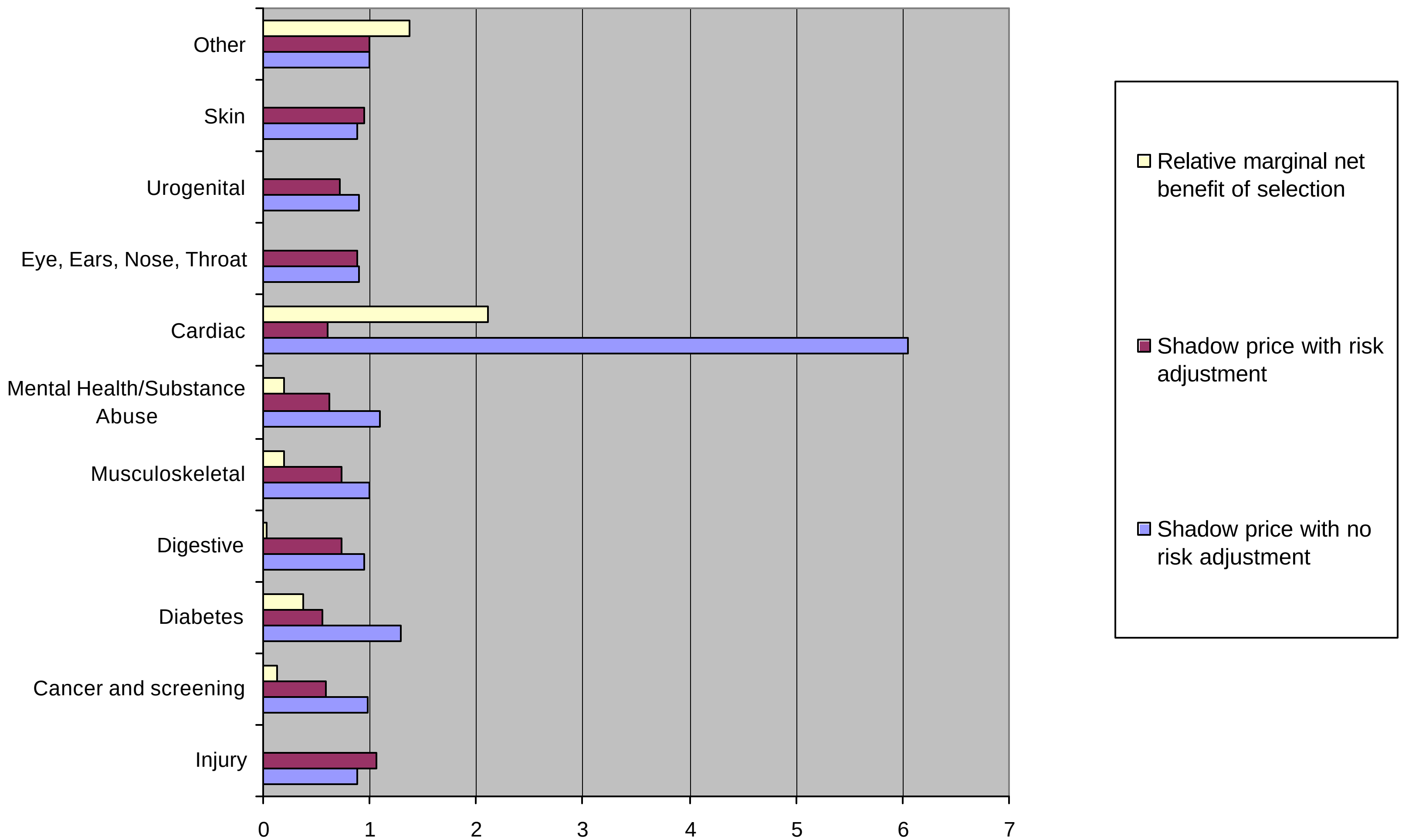


Table 4. Shadow prices for three information assumptions and two risk adjustment systems, GIC managed care and indemnity plan enrollees

	Managed Care (All HMO Enrollees)						Indemnity Plan					
	0% prior use		40% prior use		100% prior use		0% prior use		40% prior use		100% prior use	
Services	No RA	With RA	No RA	With RA	No RA	With RA	No RA	With RA	No RA	With RA	No RA	With RA
Injuries	0.741	1.152	0.886	1.062	0.903	0.700	0.783	1.022	0.923	0.997	0.915	0.554
Cancer and screening	0.789	0.831	0.982	0.583	1.024	0.403	0.878	0.889	1.048	0.618	1.018	0.333
Diabetes	0.819	0.781	1.296	0.549	1.407	0.547	0.888	0.839	1.205	0.575	1.177	0.350
Digestive conditions	0.775	0.957	0.941	0.739	0.989	0.466	0.835	0.920	0.964	0.756	0.963	0.362
Musculoskeletal conditions	0.803	0.884	0.995	0.741	1.038	0.567	0.880	0.898	1.080	0.861	1.072	0.571
Mental Health/Substance Abuse	0.740	1.072	1.101	0.615	1.146	0.569	0.756	1.081	1.291	0.957	1.198	0.915
Cardiac care	0.828	0.745	6.045	0.601	50.455	5.102	0.890	0.804	12.230	0.817	33.245	6.860
Eye, Ears, Nose, and Throat	0.757	0.966	0.899	0.884	0.908	0.605	0.835	0.939	0.938	0.868	0.898	0.462
Urogenital conditions	0.755	0.904	0.905	0.725	0.940	0.464	0.823	0.982	0.900	0.808	0.891	0.335
Skin conditions	0.760	0.969	0.891	0.956	0.900	0.637	0.827	0.933	0.937	0.927	0.912	0.499
Other conditions	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Weighted average shadow price	0.913	0.961	1.531	0.853	8.884	1.469	0.923	0.943	3.814	0.857	11.420	2.674
Premium multiplied by X% so that all services profitable	50	50	50	250	50	700	50	50	500	50	1400	150

RA = Risk adjustment (using DCG/HCC); shadow prices are relative to "other services"; % prior use is the percentage of prior year spending that the enrollees use when predicting current year spending (to assess how a health plan will meet their needs).

Figure 2. Incentive to Ration Specific Services
(GIC HMO enrollees, 40% prior use, 2PM)



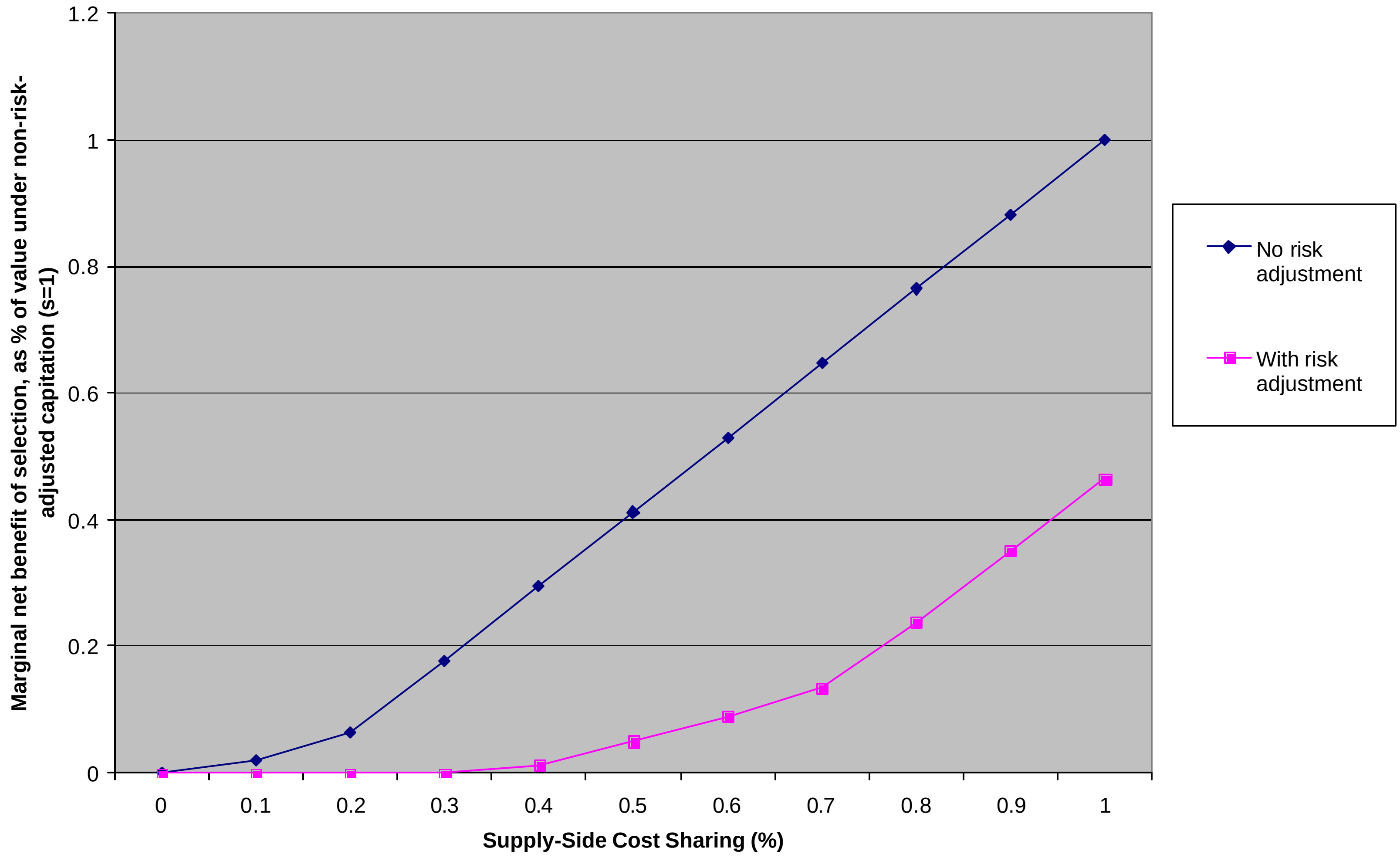
4.1 Supply-side Cost Sharing and Provider Agency

In addition to risk adjustment, another way to reduce a health plan's incentives to risk select is to used mixed payment (see Newhouse 1996, 2002). Using the GIC managed care encounter data, we empirically estimate a managed care plan's *net marginal benefit of risk selection* (see (6) and (12) above) for a range of supply-side cost sharing from capitation ($s = 1$) through forms of mixed payment ($0 < s < 1$) to pure cost reimbursement ($s = 0$). As far as we know, this is the first empirical estimate of risk selection incentives over a full range of supply-side cost sharing.

Figure 3 shows the results, with selection incentives all measured relative to those under capitation with no risk adjustment. Financial incentives to distort service quality increase with supply-side cost sharing, reaching their maximum with capitation. Empirically the returns to selection appear to be convex: reducing supply-side cost sharing from 1 to 0.5 more than halves the incentives to risk select. At $s = 0.5$—representing reimbursement of half of any given dollar's expenditure, similar to PPS (McClellan 1997)—the weighted average net marginal benefit of selection is about 40% of what it is with full capitation ($s = 1$). Another way of stating this empirically convex relationship is to say that introducing partial capitation into what had been a purely cost-reimbursement payment system can achieve substantial incentive for cost control without dramatically exacerbating risk selection.

Risk adjustment dramatically reduces selection incentives for any given level of supply-side cost sharing. Under full supply-side cost sharing (capitation), risk adjustment reduces the marginal net benefit of selection by more than half. With only 50% supply-side cost sharing, risk adjustment reduces the marginal net benefit of selection to only 5% of that under capitation with no risk adjustment. This data clearly shows the potential power of risk adjustment and mixed payment to reduce incentives for risk selection.

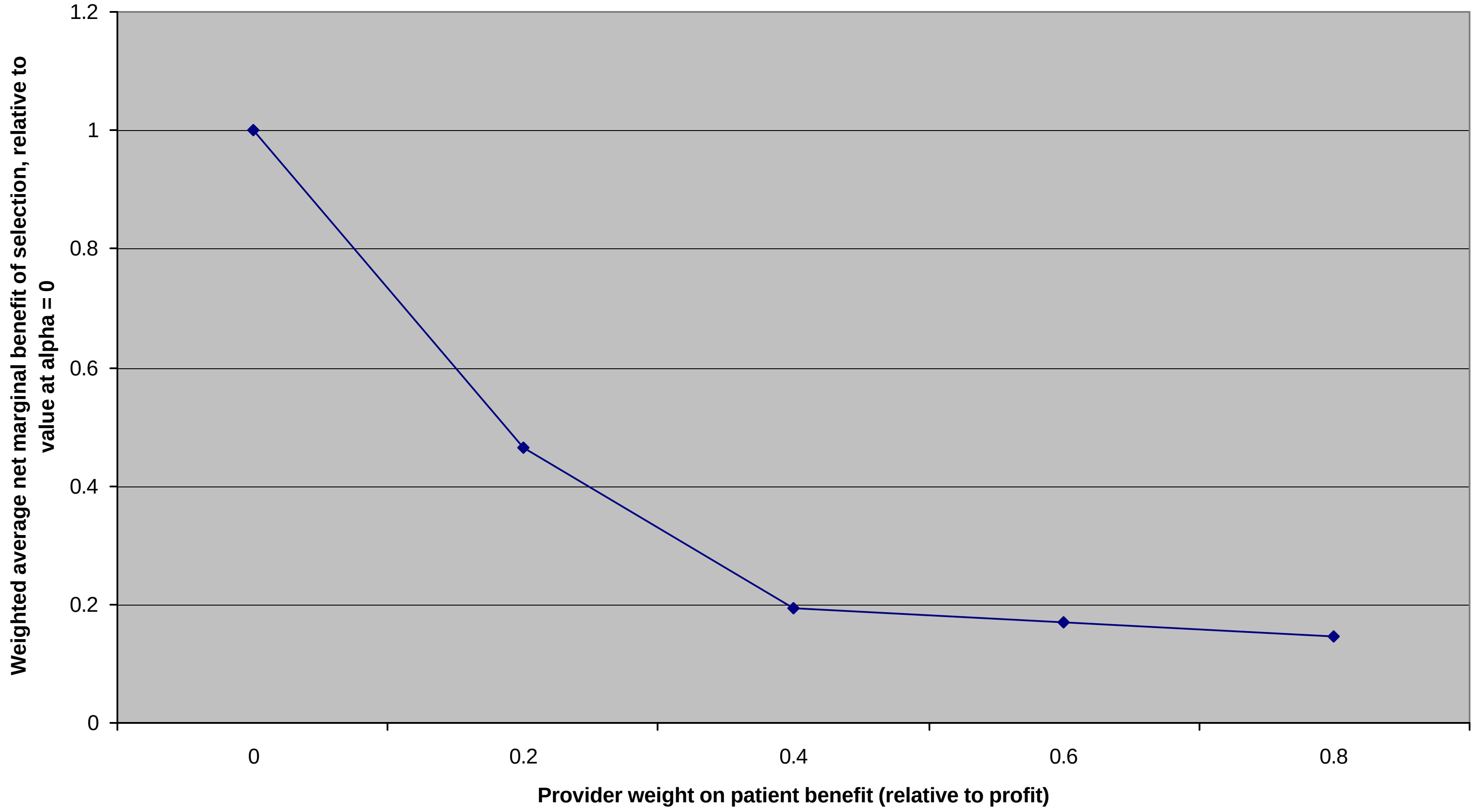
Figure 3. Selection Incentives Increase with Supply-Side Cost Sharing
(GIC HMO enrollees, 100% prior use, 2PM)



In addition to, and complementary with, risk adjustment and supply-side cost sharing, another force that can counteract risk selection is provider professional ethics or 'benevolence.' To the extent that health plans and their contracting clinicians directly value quality of care (relative to profit), they will have less incentive to distort service qualities to achieve selection. We empirically estimate the impact of benevolence by calculating the net marginal benefit of risk selection for a range of α (see (4) and the discussion after (12) above).

Figure 4 shows how provider benevolence mitigates risk selection incentives. Interestingly, as for supply-side cost sharing, the relationship is nonlinear. In other words, increasing providers' direct concern for quality more than proportionately reduces incentives to distort service quality to discourage unprofitable patients from enrolling. For high enough provider benevolence, the plan has no incentive to under- or over-provide any particular services, and wishes instead to provide exactly what the patient desires, regardless of profitability.

Figure 4. Selection Incentives Decrease with Provider Agency on Behalf of Patients
(GIC HMO enrollees, 40% prior use, 2PM)



4.2 Direct Profits from Risk Selection

Since these three selection metrics are a relatively new, we supplement the analysis with a more conventional measure: the direct profits that an insurer could achieve by excluding unprofitable enrollees (see Shen and Ellis 2002). We calculate the maximum obtainable profits when insurers exclude patients predicted to be unprofitable based on the previous year's spending and current year's premium (or risk adjustment).

The gross profit rates that a risk-selecting health plan can achieve by excluding unprofitable patients are shown in Table 5, for various assumptions about what the plan and the payer know about enrollees. The gross profit rate is total revenue less total cost, as a fraction of total revenue. Total revenue is the sum of premiums for those who enroll, i.e., those the plan predicts will be profitable given the premiums paid by the payer and the information that the plan knows about how much that enrollee will likely spend. Since in reality insurers cannot discriminate so blatantly or predict individual profitability perfectly, these profit estimates represent an upper bound on the financial returns to risk selection. Panel a shows profits for a plan serving the managed care enrollee population, whereas panel b shows the profits or losses for a plan serving the indemnity plan population.

Table 5 reveals the strong financial reward (double-digit profits) for a health plan that can figure out how to exclude unprofitable patients. Profits are generally higher, the more the plan knows relative to the payer. Indeed, if the plan knows enrollee spending in the previous year, whereas the payer uses at most age and sex to adjust premiums, then the plan can achieve a profit rate (51-55%) almost as high as if the plan could perfectly foresee each enrollee's actual spending and exclude those that will be unprofitable (67-68%). For any given assumption about what the plan and the payer know about enrollees, gross profit rates differ between the managed care and indemnity plan populations, underscoring the potency of diagnosis-based risk adjustment for the indemnity population in particular.

Table 5. Gross profit rates for a risk-selecting health plan, for various assumptions about what the plan and the payer know about enrollees

a. Gross profit rates for managed care enrollees, 2PM, (%):

Payer information set	Plan information set			
	Age + Sex	HCCs	Prior use	Actual use
0 (no adjustment)	19.5	41.6	51.2	68.3
Age + Sex	--	25.9	35.6	--
HCCs	13.8	--	35.3	59.4

b. Gross profit rates for indemnity plan enrollees, 2PM, (%):

Payer information set	Plan information set			
	Age + Sex	HCCs	Prior use	Actual use
0 (no adjustment)	17.0	40.9	55.2	67.3
Age + Sex	--	25.1	42.4	--
HCCs	-10.4	--	-2.8	42.9

Note: The gross profit rate is (Gross Profit) / (Total Revenue), where (Gross Profit) = (Total Revenue) – (Total Cost).

5 Conclusion

This study extends the theory and empirical study of health insurer selection incentives. It seems reasonable to assume that risk selection will be less of an equity and efficiency concern when insurers care about things besides pure profit, or when insurers share the risk of financial losses with payers. To test these conjectures theoretically and empirically, we incorporate insurer nonfinancial concerns and partial supply-side cost sharing into the empirically implementable shadow price index proposed by Frank, Glazer and McGuire (2000). We also propose a new metric of selection incentives, the *net marginal benefit of risk selection (NetMB),* to complement the shadow price estimates. This selection index captures the financial reward to insurers for deviating from socially-optimal care. We compare these results to the selection index developed by Ellis and McGuire (2004) based on a service's predictability and predictiveness.

We calculate all three measures of selection using managed care medical and pharmacy spending data for fiscal years 2001 and 2002 from the Massachusetts state employee insurance program. The empirical results reveal strong financial returns to risk selection, as indicated both by the three selection indices and by the direct profits an insurer could earn if it could exclude unprofitable patients. Services most vulnerable to stinting are cardiac care, diabetes care and mental health and substance abuse services. The net marginal benefit of risk selection increases nonlinearly with supply-side cost sharing, reaching a maximum with capitation. Thus empirical evidence confirms that forms of mixed payment (such as partial capitation) soften risk selection incentives.

Our empirical estimates also show that adherence to professional ethics mitigates selection incentives. We simulate this effect by calculating the net marginal benefit of selection as we increase the hypothetical weight that an insurer puts on patient benefit (i.e., quality) relative to profit. As for supply-side cost sharing, the estimated relationship is nonlinear: increasing providers' direct concern for quality more than proportionately reduces incentives to distort service quality.

This analysis of managed care encounter data suggests that the Ellis-McGuire selection index, shadow prices, and the intermediate selection index proposed herein can be useful for examining insurers' financial incentives to distort services to attract profitable enrollees. As a tool for measuring selection incentives, these approaches have several advantages. First, they are more quantifiable and evidence-based that two common other approaches to identifying perverse incentives: the case-by-case or anecdotal approach, and deductive reasoning regarding all-encompassing categories (e.g., overuse with fee-for-service, underuse with capitation). Second, analysts can tailor the measurement of selection incentives to specific patient populations (e.g., by using the specific expenditure and diagnosis patterns of that population). Third, employers and other purchasers can analyze various alternative payment methods prior to implementation to examine alignment of payment incentives with quality improvement. This may contribute to better contracting and clearer targetting of quality assurance programs. Fourth, such analyses can help researchers to identify the weaknesses and strengths of different risk adjustment and risk sharing systems. Fifth, these selection indices identify potential quality problems without being accusatory (and could not be used by lawyers as material for discovery).

The methodology for identifying perverse incentives for quality distortions should be broadly applicable (at least for employers and other purchasers that have managed care encounter data), even though the data in this study is not nationally representative. Further research on these selection indices could help to reveal their relative merits. Fruitful extensions might include examining more detailed service categories with a larger sample, and simulating additional purchasing strategies to mitigate selection, such as carve-outs, high-risk pooling, and supply-side cost sharing that varies across services. Finally, these metrics of selection *incentives* should be complemented by studies that quantify the extent of *actual* selection-motivated quality distortions and how they are affected by initiatives like mixed payment and pay-for-performance.

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