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

Karen Eggleston
Anupa Bir

Abstract

Capitation gives insurers incentive to manipulate their offerings to attract the healthy and deter the sick. We calculate the incentives for such service-specific quality distortions using managed care medical and pharmacy spending data for fiscal years 2001 and 2002 from the Massachusetts State Employee Insurance Program. Services most vulnerable to stinting are cardiac care, diabetes care, and mental health and substance abuse services. Empirically, the financial temptation to distort service quality increases nonlinearly with supply-side cost sharing. Our empirical results highlight how selection incentives work at cross-purposes with efforts to reward excellent chronic disease management. Initiatives coupling pay-for-performance with risk adjustment and mixed payment hold promise for aligning incentives with quality improvement.

Introduction

Capitation payment—or any payment featuring "supply-side cost sharing" (Ellis and McGuire, 1990)—gives health plans and providers the 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, 2000).[1] When health plans compete to avoid the sick rather than provide quality care, the most vulnerable patients may experience access problems, and all patients suffer from the selection-motivated

Karen Eggleston is with Shorenstein Asia-Pacific Research Center, Stanford University, Stanford, CA. Anupa Bir is with RTI International. The authors can be contacted via e-mail: karene@stanford.edu and abir@rti.org, respectively. We gratefully acknowledge research support from The Robert Wood Johnson Foundation's Changes in Health Care Financing and Organization (HCFO) Initiative, Grant No. 47325. We thank Ann Larsen for excellent programming assistance and Gregory Pope, Richard Zeckhauser, and two anonymous referees for constructive comments. All remaining errors are our own.

[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).

distortions in quality. Selection may also prevent individuals from being able to buy insurance against becoming a bad risk in the future (Newhouse, 1996; Feldman and Dowd, 2000). Selection thus poses problems of both efficiency and equity.

Some societies embrace single-payer systems, which help to minimize selection concerns. Within multipayer systems, employers and other purchasers often enforce open enrollment periods, proscribe preexisting conditions clauses, and stipulate standard benefit packages. Yet competing insurers 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 (Frank, Glazer, and McGuire, 2000).[2]

In this article, we estimate empirically how a profit-maximizing insurer would want to distort service offerings to attract profitable enrollees. For example, a health plan may find it financially rewarding to limit access to "indicator treatments" that attract less profitable patients, such as chronic disease management, but encourage access to services used by relatively profitable patients, such as preventive or acute care. Nonprice mechanisms may include waiting time, geographic accessibility, and other dimensions of convenience as well as payment incentives to clinicians.[3]

The theory of service-specific quality distortions was developed to measure selection incentives in managed care, yet it has not yet been applied to managed care data; we do so.[4] Our data include claims and managed care encounter data including 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 health care purchasers in New England.

Our empirical results highlight how selection incentives work at cross-purposes with efforts to reward excellent chronic disease management. Insurers have financial disincentives to provide high-quality cardiac services, diabetes management, or treatment for mental health and substance abuse problems. Thus, plans that gain a reputation for quality disease management programs in these areas face a financial penalty through attracting an adverse risk pool. This selection effect further reduces the return to investing in disease management, already demonstrated to have a low overall return to a plan over a decade interval for some diseases such as diabetes (Beaulieu, Cutler, and Ho, 2005).

[2] Also see Glazer and McGuire (2001, 2002a, b), Cao and McGuire (2003), and Ellis and McGuire (2004).

[3] In the income-transfer literature, such nonprice mechanisms are sometimes referred to as *ordeals*. Regulators can impose ordeals—such as otherwise unnecessary waiting times—to improve target efficiency of welfare programs (Nichols and Zeckhauser, 1982); firms can use ordeals to select profitable clients, similar to the quality distortions used for risk selection discussed here.

[4] In the original empirical application of this approach to measuring selection incentives in managed care, Frank, Glazer, and McGuire (2000) 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 3 years (1991–1993). These results do not represent the privately insured population nor do they reflect the impact of managed care.

Risk adjustment can be an effective tool to combat selection. We find that risk adjustment considerably mitigates selection incentives for this population.[5] The GIC's recent move toward all-encounter health-based risk adjustment among its plans is thus well warranted. Unfortunately, however, risk adjusters remain imperfect and little used (see discussion in van de Ven and Ellis, 2000; Newhouse, 2002).

Economic theory also 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, 2002; Ma and McGuire, 1997; Eggleston, 2000; Pauly, 2000), 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. These empirical results clearly show that mixed payment can be effective in reducing the incentives for risk selection while still promoting cost control.

Finally, we estimate the direct profits that an insurer could achieve by excluding unprofitable enrollees. 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 percent to over 50 percent. Profits are generally higher the more the plan knows relative to the payer.

Together these results underscore the financial temptation for insurers to invest in risk identification and selection. Such strong selection incentives reinforce the policy importance of coupling pay-for-performance with risk adjustment and mixed payment to promote quality improvement, especially for those chronic diseases that otherwise would attract an unprofitable patient case mix.

Our empirical estimates quantify the financial *temptation* to engage in risk selection; they do not measure the extent to which selection is actually taking place. Research quantifying the extent to which insurers and providers respond to these financial incentives is an important complementary undertaking.

The article is organized as follows. We preface the empirical analysis with a brief conceptual discussion of selection incentives.[6] We then discuss the data and empirical strategy and present our empirical results. We conclude by summarizing our findings and suggesting the potential usefulness of selection metrics for employers and other purchasers.

CONCEPTUAL BACKGROUND

Selection Incentives in Managed Care

Let us assume that "managed care" relies predominantly on various supply-side rationing measures rather than patient copayments to control spending. Managed

[5] This finding is consistent with 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).

[6] See Eggleston and Bir (2005), available at http://ase.tufts.edu/econ/papers/papers.html, for details on the theory of managed care, selection indices definitions, and the other methodological building blocks of the article.

care organizations competing for enrollees face a trade-off when deciding how stringently to ration access to different services (Frank, Glazer, and McGuire, 2000). Stringent rationing benefits the insurer by reducing spending per enrollee and discouraging high-cost individuals from enrolling. But it also may discourage profitable patients from joining the plan and damage the insurer's reputation.

Payment is often more generous for some services or patients than others. These financial incentives will shape the plan's desire to promote quality for specific services. Which services are unprofitable will depend on several factors, including the level of the (possibly risk-adjusted) payment, enrollees' patterns of service utilization, and the degree of supply-side cost sharing for each service.

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 et al., 2001).[7] Supply-side cost sharing helps to control spending but gives plans the 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 " quality-distortion selection." Higher supply-side cost sharing induces more quality-distortion selection.

Different degrees of supply-side cost sharing for different services could improve incentives relative to uniform payment. However, at present payers rarely vary supply-side cost sharing by service. Perhaps such variation is currently too administratively cumbersome to be practical, or payers are unclear what amount of cost sharing would be optimal for each service. Even without such variation in payment, however, employers and other purchasers can use information about "vulnerable services" in applying a whole gamut of purchasing strategies, including pay-for-performance and quality monitoring. A purchaser that discovers diabetes care to be extremely vulnerable to selection-motivated quality distortions, for example, could target pay-for-performance bonuses and quality monitoring time and effort on that service.[8] In this article we use empirically estimable selection indices to quantify selection incentives that may help guide purchasers with such decisions.

Empirically Estimating Selection Incentives

Ellis and McGuire (2004) propose a selection index based 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 the incentive to ration services that are predictable and associated with high total cost. Let $\hat{m}^i_j$ denote consumer i's

[7] 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.

[8] 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.

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.

Predicted spending $\widehat{m}_j$ depends on how much information individuals have and use when choosing health plans. Frank, Glazer, and McGuire (2000) 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 percent). We estimate predicted spending assuming individuals predict future spending based on (100 percent) prior use and contrast that with predicted spending based only on age and sex.

To aggregate selection incentives across services (without the problematic assumptions necessary for shadow prices; see discussion in Eggleston and Bir, 2005), we propose a measure called the *net marginal benefit of risk selection* (*NetMB*). It 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 the 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 ($\frac{\widehat{m}_j}{M}$):

$$NetMB = \sum_j \left(\frac{\widehat{m}_j}{M}\right) \mathrm{Max}\left[NetMB_j, 0\right], \tag{1}$$

where

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

$$\widehat{m}_j = \frac{\sum_i \widehat{m}_j^i}{N}; \quad r = \frac{\sum_i r^i}{N};$$

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

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

$$\bar{s} \equiv \frac{\sum_j s_j \widehat{m}_j}{\sum_j \widehat{m}_j}; \text{ and } \widehat{M} = \sum_j \widehat{m}_j.$$

In this formula, $\widehat{m}_j$ 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 Frank, Glazer, and McGuire, 2000; $r^i = 1.5r^i_{HCC}$); $\widehat{\sigma}_j$ 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 $j'; \bar{s}$ 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.

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).[9] 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: $E\pi = r(\bar{s}) - \bar{s}\widehat{M}, = 0.5\widehat{M}$, so that $r(\bar{s}) = (0.5 + \bar{s})\,\widehat{M}$.[10]

DATA AND EMPIRICAL STRATEGY

Our data include claims and managed care encounter data, including diagnoses and medical and pharmacy spending, from the 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 (PPO), 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. For more details 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. Annual enrollment changes for GIC beneficiaries become effective in July.

[9] 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.

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

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" subsample (65,615 enrollees), we included all continuously enrolled,[11] nonelderly 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 subsample of nonelderly adults continuously enrolled in the indemnity plan (86,365).[12]

The spending variable represents total covered charges, including patient out-of-pocket payments.[13] We examined selection incentives with 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 use a mixture of chronic and acute conditions, with a sizable percentage of enrollees (no fewer than 10 percent) utilizing each service in each year.[14] 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

[11] 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.

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

[13] 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 deducting third-party, copayment, coinsurance, or deductible amounts.

[14] The categories replicate the strategy employed by Frank, Glazer, and McGuire (2000) but not their exact service categories because not all are as appropriate for our sample as for their Medicaid sample. (For example, birth services were a large category for Frank, Glazer, and McGuire's Medicaid sample but not for our sample.)

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	1,520.02	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	1,296.47	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	1,081.71	138.31	5.3	0.031	0.538
Cardiac care	18.6	1,287.61	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	1,076.39	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	1,645.11	310.50	6.0	0.153	0.097
Cancer and screening	29.3	2,420.21	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	1,880.48	371.03	7.1	0.044	0.077
Musculoskeletal conditions	40.4	1,660.89	671.61	12.9	0.051	0.323
Mental health/ substance abuse	12.5	1,655.00	206.65	4.0	0.037	0.522
Cardiac care	30.9	2,339.50	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	1,470.36	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	1,504.72	1,102.19	21.2	0.192	0.313

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.

Calculating selection indices 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 not 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 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 subsamples. 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 subsample. Third, we use the prediction subsample 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. (Results with ordinary least squares were broadly similar.)

Table 2 shows the correlations between actual and predicted spending with our different information assumptions. Correlations are much higher when individuals use prior spending to predict current spending. Diabetes, mental health and substance

TABLE 2
Correlations Between Actual and Predicted Spending With Different Information Assumptions

	Managed Care		Indemnity Plan	
Service	Age, Sex	Age, Sex, Prior Use	Age, Sex	Age, Sex, Prior Use
Injuries	0.00	0.22	0.01	0.12
Cancer and screening	0.02	0.22	0.04	0.31
Diabetes	0.05	0.44	0.06	0.28
Digestive conditions	0.03	0.28	0.02	0.09
Musculoskeletal conditions	0.07	0.32	0.05	0.34
Mental health/substance abuse	0.02	0.53	0.03	0.52
Cardiac care	0.10	0.23	0.08	0.21
Eye, ears, nose, and throat	0.02	0.27	0.03	0.31
Urogenital conditions	0.05	0.34	0.01	0.27
Skin conditions	0.02	0.30	0.01	0.12
Other conditions	0.08	0.25	0.03	0.21

Note: Information assumptions refer to what information individuals use when predicting current year spending (to assess how a health plan will meet their needs): average spending on each service for someone of the same age and sex, or predicted spending based on age, sex and their own prior-year spending on each service.

TABLE 3
Ellis–McGuire Selection Index, GIC Indemnity and HMO Enrollees

	Indemnity			HMO		
Name	CV	corr($\widehat{m}$, M)	Selection Index	CV	corr($\widehat{m}$, M)	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 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

Notes: CV = coefficient of variation of service-specific predicted spending (standard deviation/mean); corr($\widehat{m}$, M) = correlation between predicted spending on that service and total spending.

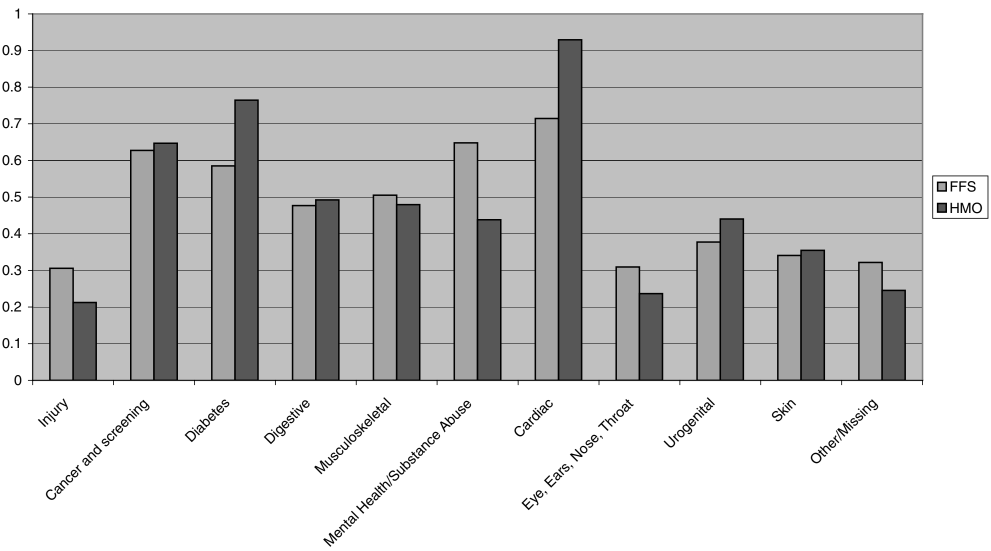
abuse, and musculoskeletal condition spending are the most predictable with prior use; injuries are among the least predictable services.

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

RESULTS

Analyses reported in Table 3 and Figure 1 reveal that the most at-risk services are cardiac, diabetes, and cancer care for the HMO population, and cardiac, mental

FIGURE 1
Ellis–McGuire Selection Index (GIC HMO and Indemnity Plan Enrollees, 100% Prior Use, 2PM)

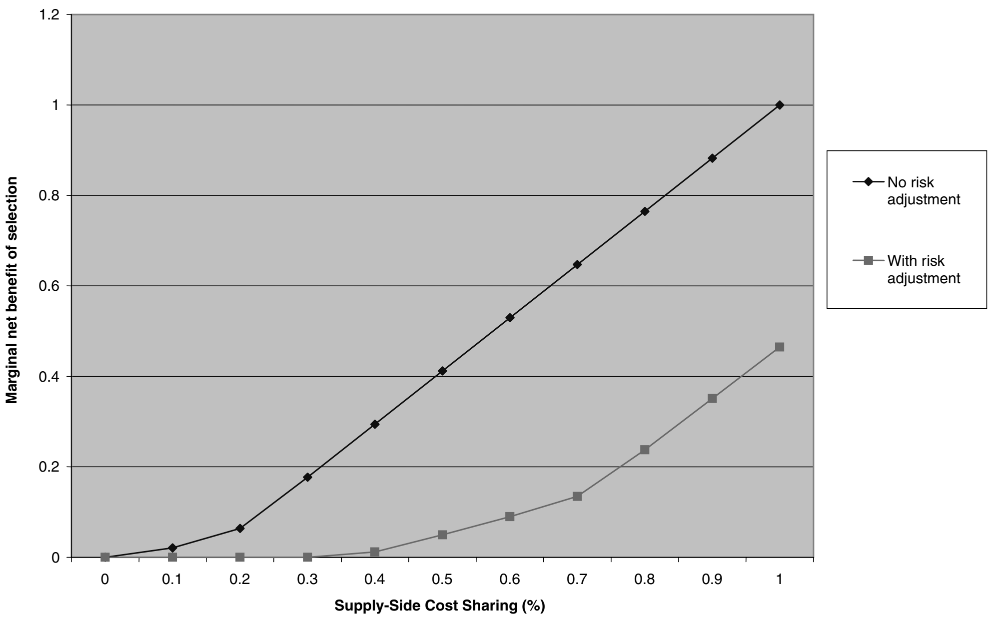


health/substance abuse, cancer, and diabetes care for the fee-for-service population. The plan has the least incentive to distort services for injuries and conditions of the eyes, ears, nose, and throat. As the descriptive statistics suggested, the coefficient of variation for mental health and substance 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.

Risk adjustment, mixed payment, and regulation are complementary tools that diminish a health plan's incentives to risk select. Using the GIC managed care encounter data, we empirically estimate a managed care plan's *net marginal benefit of risk selection* (see (1) 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 2 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 a Prospective Payment System (McClellan, 1997)—the weighted average net marginal benefit of selection is about 40 percent of what it is with full capitation ($s = 1$).

FIGURE 2
Selection Incentives Increase With Supply-Side Cost Sharing (GIC HMO Enrollees, 100% Prior Use, 2PM)



Note: The marginal benefit of selection is measured as the percentage of the marginal benefit under full capitation ($s = 1$) with no risk adjustment.

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 significantly 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 percent supply-side cost sharing, risk adjustment reduces the marginal net benefit of selection to only 5 percent of that under capitation with no risk adjustment. These data clearly show the potential power of risk adjustment and mixed payment to reduce incentives for risk selection.

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 4, 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

TABLE 4
Gross Profit Rates for a Risk-Selecting Health Plan, for Various Assumptions About What the Plan and the Payer Know About Enrollees

	Plan Information Set			
Payer Information Set	Age + Sex	HCCs	Prior Use	Actual Use
Panel A. Gross Profit Rates for Managed Care Enrollees				
0 (no adjustment)	19.5%	41.6%	51.2%	68.3%
Age + Sex	–	25.9%	35.6%	–
DCG/HCC risk adjustment	13.8%	–	35.3%	59.4%
Panel B. Gross Profit Rates for Indemnity Plan Enrollees				
0 (no adjustment)	17.0%	40.9%	55.2%	67.3%
Age + Sex	–	25.1%	42.4%	–
DCG/HCC risk adjustment	−10.4%	–	−2.8%	42.9%

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

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. Because 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 4 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 percent) almost as high as if the plan could perfectly foresee each enrollee's actual spending and exclude those that will be unprofitable (67–68 percent). 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.

CONCLUSION

For a general employed population, risk selection incentives discourage quality care for expensive chronic conditions, such as cardiac care and diabetes. Using managed care medical and pharmacy spending data for fiscal years 2001 and 2002 from the Massachusetts State Employee Insurance Program, we find strong financial returns to risk selection. Services most vulnerable to stinting are cardiac care, diabetes care, and mental health and substance abuse services.

Empirical evidence also confirms that forms of mixed payment (such as partial capitation) soften risk selection incentives: the net marginal benefit of risk selection increases nonlinearly with supply-side cost sharing, reaching a maximum with capitation. Risk adjustment mitigates selection effects, especially for high levels of supply-side cost sharing.

As a tool for measuring selection incentives, this approach has several advantages. First, these selection indices are quantifiable and evidence based. 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).

These empirical estimates quantify the financial *temptation* to engage in risk selection; they do not measure the extent to which selection is actually taking place. Research on the extent to which insurers and providers respond to these financial incentives is an important complementary undertaking. For example, 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 decision making too stringently. Professional ethics among providers can thus also limit insurer efforts to cater exclusively to profitable enrollees. These considerations all reduce the extent to which insurers act upon risk selection incentives.[15]

The methodology we use to identify 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. Fruitful extensions would examine more detailed service categories with a larger sample, simulate additional purchasing strategies to mitigate selection (such as carve-outs, high-risk pooling, and supply-side cost sharing that varies across services), and quantify actual selection-motivated quality distortions and how they differ by organizational form or in response to mixed payment or pay-for-performance.

Our empirical results highlight how selection incentives work at cross-purposes with efforts to reward excellent chronic disease management. Initiatives coupling

[15] 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. See Eggleston and Bir (2005) for a simulation of how adherence to professional ethics mitigates selection incentives, and Eggleston and Yip (2004) for an explicit model of plan-physician contracting and physician choice of spending levels for each patient.

pay-for-performance with risk adjustment and mixed payment hold promise for aligning incentives with quality improvement.

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