Demand elasticities and service selection incentives among competing private health plans

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Abstract: We examine selection incentives by health plans while refining the selection index of McGuire et al (2014) to reflect not only service predictability and predictiveness but also variation in cost sharing, risk-adjusted profits, profit margins, and newly-refined demand elasticities across 26 disaggregated types of service. We contrast selection incentives, measured by service selection elasticities, across six plan types using privately-insured claims data from 73 large employers from 2008 to 2014. Compared to flat capitation, concurrent risk adjustment reduces the elasticity by 47%, prospective risk adjustment by 43%, simple reinsurance system by 32%, and combined concurrent risk adjustment with reinsurance by 60%. Reinsurance significantly reduces the variability of individual-level profits, but increases the correlation of expected spending with profits, which strengthens selection incentives.

Keywords: health insurance, risk selection, risk adjustment, reinsurance, health care demand elasticities. (*JEL:* I11, C21, D12)

Introduction

Under fixed premiums, health plans have incentives to prefer enrolling healthy, low-cost rather than sicker, high-cost enrollees, since premiums do not reflect the full cost differential between sick and healthy enrollees. While governments and employers can regulate plan benefits, and prohibit explicit exclusion of people based on costs or preexisting conditions, it is more difficult to regulate service-level selection, the supply-side availability of provider specialties or types of services. Service-level selection is particularly easy when health plans can design plan benefits such as cost sharing or influence the availability of specific services, in order to attract or deter enrollees expecting to use those services. Risk adjustment, in which plan revenues depend on the age, gender and diagnoses of their enrollees, and reinsurance, in which plans are partially compensated *ex post* for their highest-cost individual patients, are important strategies that can be used to reduce service-level selection incentives, but uncertainties remain about how well they do so.

This paper builds upon the recent literature on service-level selection and makes three contributions. First, we refine the analytical framework to better reflect variation in service-level cost sharing paid by consumers, and premium markups that result in nonzero profits, which can influence plan profits and selection. Second, we improve the empirical measure of service-level selection incentives by including new estimates of service-level demand elasticities, individual-level profit variation, and demand for health insurance in the calculation. Third, we evaluate how well various regulatory strategies reduce selection incentives: prospective risk adjustment, concurrent risk adjustment, individual-level reinsurance and a combination of reinsurance and concurrent risk adjustment.

Our framework is rooted in the service-level selection literature pioneered by Glazer and McGuire (2000) who propose and derive formulas for optimal risk adjustment payments to health plans so as to best offset service-level selection incentives. Frank, Glazer and McGuire (2000) extend this framework by explicitly modeling profit maximizing service-level spending in the absence of optimal risk adjustment. They also develop an empirical measure of the incentive to select, and use US Medicaid data to demonstrate that selection incentives vary dramatically across services. By making further simplifying assumptions, Ellis and McGuire (2007) (henceforth EM) derived a selection index that was the product of predictability (i.e., how well individuals can predict their subsequent use of each service) and predictiveness (i.e., how well expected spending on each service predicts plan profitability), making the index easier to interpret empirically. Ellis, Jiang and Kuo (2013) examined whether prospective, diagnosis-based risk adjustment reduces selection incentives in a study of the privately insured, using an earlier version of the data used here.[1] A weakness of EM and EJK is that both studies calculate empirically only two terms - predictability and predictiveness - in the selection index, and ignore or assume constant the rest of the terms. McGuire et al (2014) was the first to correct this weakness, by incorporating demand-side cost sharing in their analysis, allowing demand elasticities to vary by type of service, and exploring the effect of multiple health plan payment policies, which reflect both risk adjustment and reinsurance. In this paper, we refine the index of McGuire et al (2014) and calculate the full selection elasticity, which reflects five terms beyond predictability and predictiveness: (1) demand-side cost sharing, (2) service-level demand elasticities, (3) individual-level profit variation, (4) actual profit levels, and (5) demand responsiveness of health insurance enrollment to expected spending. We show below how these

[1] Layton et al. (2017) (LEMvK) provide an overview of the literature on service-level selection and evaluate alternative premium, risk adjustment, and reinsurance systems. They separately develop welfare-based measures that can be used to evaluate demand-side premiums, supply-side revenue, and incentives for service selection.

five terms interact with the EM predictability and predictiveness terms and can affect the magnitude and relative importance of selection incentives across services and under alternative payment systems.

Service-level demand elasticities were ignored in the EM selection index largely due to a lack of the empirical estimates of them at the detailed type of service level.[2] Here, we take advantage of the results from Ellis, Martins and Zhu (2017) (henceforth EMZ) who develop a new instrumental variables method for estimating demand elasticities at the detailed type of service level. Using the identical sample as is used in this paper, EMZ focus their analysis on within-year variation in cost sharing, taking advantage of differences between plans such as preferred provider organizations (PPOs) and health maintenance organizations (HMOs) where cost sharing is often constant during the year and plan types like high deductible health plans (HDHPs) and consumer-driven health plans (CDHPs) where cost shares can change dramatically during the year. The key insight in their work is that although an individual's cost share is endogenous to their own health status and prior spending, the average of other people at the same firm is exogenous to the consumer's choice, and forms a valid instrument. Section IV provides an overview on how EMZ results are obtained empirically and used in this paper.

We use US employer-based health insurance data to implement our service-level selection framework and simulate different payment systems. While neither risk adjustment nor reinsurance is currently in place for the employer-based insurance market, simulations using this data shed light on variations in service selection incentives and how payment policies change those incentives.

[2] McGuire et al (2014) take a step forward in their calculation of the demand elasticities in that they allow them to vary across services. They assume two different levels of elasticities among the seven types of services they consider: -0.4 for mental health and substance abuse services, and -0.2 for everything else.

To give a preview of our results, we find that incorporating cost sharing, demand responsiveness and profit variation into our selection calculations makes meaningful changes: higher cost sharing services become less attractive to underprovide, while more demand elastic services (e.g., pharmaceuticals) become more attractive to distort relative to inelastic services (e.g., prevention). We find that concurrent diagnosis-based risk adjustment (using only current year information) makes only a modest improvement in selection incentives relative to prospective models (using only information from the previous year), despite a much higher R^2. Both risk adjustment models appear to perform better than simple reinsurance at mitigating selection incentives, even though reinsurance achieves a higher R^2 than either concurrent or prospective risk adjustment. Our analysis of the underlying components of the selection formula also suggests why this is so: by eliminating some of the noise in the upper spending tail, reinsurance tends to increase the positive correlation between service-level spending and reinsured total spending, hence improving the predictiveness of some services, and hence the desirability of underproviding those services.

The rest of the paper is structured as follows. Section I provides an introduction to the US health plan types, with a focus on their varying degrees of restrictions on patient choice of providers or services, the resulting selection incentives and efforts to mitigate them. Section II reviews the Selection Index in EM and McGuire et al (2014) which form the basis of our new full selection elasticity (FSE). The data used for this study is summarized in Section III, while Section IV describes the estimation strategy. Section V presents our empirical results. Section VI includes brief concluding remarks as well as suggestions for future research.

I. Background

Recent theoretical and empirical studies in the health care literature, summarized in Layton et al (2017), have focused on identifying and correcting service-level selection incentives, by which we mean the incentives to influence enrollee types by over- or under-supplying certain health care services. Service distortions are of particular concern with managed care health plans that are more closely involved in selective contracting with providers. In the US, a rich array of health plan types have emerged that differ in the extent to which they encourage or discourage use of specific health care services by consumers, and this variation provides a natural experiment for examining how plans with alternative management contracts differ in the services they offer. Among the traditional types of health plans, comprehensive plans (COMP) place the least restrictions on patient choice of providers or choice of services: patients can for the most part visit any provider at any time and will have coverage for almost any services. Substantially less free are health maintenance organizations (HMOs) which selectively contract with a subset of doctors and hospitals in an area, and often require *ex ante* preauthorization or *ex post* justification of services received. In between these two extremes, preferred provider organizations (PPOs) generally use selective contracting with certain but not all providers and generally arrange provider discounts to control costs. Point of service (POS) plans generally combine management services of HMOs with relatively unrestricted access to providers outside of the negotiated provider network, and hence represent a form of managed care that is looser than HMOs but tighter than PPOs or COMP.

The last ten years, in particular, have seen a rapid growth in offerings of new plan types that allow even greater opportunity for service selection. In contrast to HMOs, PPOs, and POSs, consumer-driven health plans (CDHPs) and high deductible health plans (HDHPs) charge both higher deductibles and higher coinsurance rates, which may allow favoring or discouraging services selectively through their benefit coverage. A key research question that we address is whether narrow provider panels (HMOs) or stingy benefit designs (CDHPs and HDHPs) are more effective at reducing the attractiveness of a health plan to high cost individuals via service-level selection incentives.

In order to reduce selection problems, it is common to use diagnosis-based "risk adjustment" to change incentives, where diagnostic information is combined with selected demographic variables to predict annual spending, and these predictions are used to reallocate money between competing health plans. Prospective models use only information prior to the start of the prediction period, while concurrent models use information for predicting spending from the same period as spending is being set (Ash et al. 2000). Both types of diagnosis-based models have substantially higher predictive power than models using only age and gender (van de Ven and Ellis 2000).

Whereas risk adjustment is an *ex ante* strategy to affect selection incentives, reinsurance is an *ex post* strategy whereby insurers are fully or partially insured against the risk of covering individuals who are extremely expensive *ex post*. Reinsurance is adopted by the Medicare Part D prescription drug program, as well as the ACA Health Insurance Marketplace program during the first three years. In 2014 the Marketplace program reinsures plans for 80 percent of the cost of individuals when they exceeded $60,000, which we examine in our analysis below, with and without using risk adjustment.

We conduct our analysis using a sample of privately-insured health plan enrollees to study selection incentives even though incentives for selection under employment-based insurance differ from those with individual-level plan selection, such as in the Medicare Advantage and ACA Health Insurance Marketplace. Under employment-based insurance the employer typically chooses whether to offer one or multiple plans, and may prescribe plan features, both on the demand and supply sides. Insurers may also internalize some of the plan selection incentives by offering two or more competing products, so that there is less incentive to worry about avoiding or attracting a given enrollee. Premiums often vary more than in public programs where premiums are based on pre-specified risk adjustment or age-gradient formulas. While many employer-sponsored health plans do not bear financial risk for their enrollees, it is still informative to examine selection incentives and their consequences in this data. Selection incentives are relevant in our privately-insured sample because more than 85 percent of the employer years offer multiple health plans, with the median employer offering three health plans. Even for employers offering only one plan, selection issues remain important for influencing prospective employees and health plan enrollment of employees' family members.

II. The Ellis-McGuire (EM) Selection Index and Full Selection Elasticity (FSE)

Our theoretical model builds on the EM selection index (also used by EJK) and the McGuire et al (2014) refined selection model, which we re-derive here with further refinements. First, we allow for variation in service-level elasticities of demand, which are assumed constant in the EM and EJK formulations and are only allowed to vary at two levels for seven coarse categories of services in McGuire et al (2014). Second, we refine the selection index to accommodate differences in demand-side cost sharing between services. Third, we examine how selection incentives are affected by the payment system, which includes changes in risk adjustment and reinsurance. In our simulations, the payment system can affect both the standard deviation of individual-level profitability and the service-level predictiveness.[3] As we show below, this profit variation can affect both the magnitude and the rank ordering of selection incentives across services, and hence is important when comparing selection incentives across different payment programs. Finally, we provide estimates for the other two components in FSE previously assumed constant - actual health plan profits and the demand responsiveness of plan enrollment to expected spending.

Following EM and McGuire et al (2014), we assume that a regulator (or sponsor) makes actuarially fair payments to all health plans, which means that premiums and payments are calculated to exactly equal expected costs. Implicit in this framework is the assumption that health plans are competitive, and take the offerings of other plans as given when choosing how generously to offer various services. Assume that there are *S* services offered by each health plan and that individuals respond to health plans' service-level offerings when choosing plans. Health plans anticipate this consumer responsiveness, and tighten or loosen the availability of services in order to attract profitable individuals and avoid unprofitable ones.

Individuals choose their health plan to maximize utility. Let $\hat{m}_{is}$ denote the amount that individual i *expects* the plan will spend on providing service s and let $\hat{m}_i = \{\hat{m}_{i1}, \hat{m}_{i2}, ..., \hat{m}_{iS}\}$ be the amount that individual i *expects* the plan will spend on all services. Let $m_i = \{m_{i1}, m_{i2}, \dots, m_{iS}\}$ be the corresponding amount that the plan *actually* spends on individual i, and OOP_i be the out-of-pocket payments incurred by individual i.

We assume that the utility of individual i from a plan[4] can be written as

$$u_i(\widehat{m}_i) = v_i(\widehat{m}_i) - OOP_i + \mu_i \tag{1}$$

[3] EJK and McGuire et el (2014) also examine incentives with risk adjustment, but do not compare across various payment systems that include reinsurance.

[4] We avoid giving plan index suffixes to simplify model notation, but the implications are clear.

where $v_i(\widehat{m}_i)$ is the individual's deterministic gross utility from joining the plan. Following EM, assume that $v_i(\widehat{m}_i) = \sum_s v_{is}(\widehat{m}_{is})$, i.e., the utility from consuming each service is additively separable in expected spending on each service. The second term captures the idea that the individual gets disutility from out-of-pocket payments which we explicitly model here to extend the previous literature. Similarly, assume that $OOP_i = \sum_s c_s \widehat{m}_{is}$, i.e., the total out-of-pocket payments are the sum of out-of-pocket payments across all services which equals the average service-specific cost share, c_s, for each service times the expected spending for that service, $\hat{m}_{is}$.[5] The first two terms both imply zero cross-price effects. The final term μ_i is a random term with distribution function Φ_i. The individual i chooses this plan if $u_i(\widehat{m}_i) > \bar{\mu}_i$, i.e., $\mu_i > \bar{\mu}_i - \sum_s v_{is}(\widehat{m}_{is}) + \sum_s c_s \widehat{m}_i(q_s)$, where $\bar{\mu}_i$ corresponds to the reservation utility the individual places on the next best plan.[6]

We assume that the competitive health plan maximize its profits using shadow prices to efficiently ration the amount of each health care service that each patient receives. Let $q = \{q_1, q_2, \dots, q_S\}$ denote the vector of shadow prices a plan sets for services. Following Glazer and McGuire (2000) and EM, and building on the insights of McGuire et al (2014), we use the property that the health plan's profit maximizing choice of q_s, for rationing the services $\hat{m}_{is}$ that the patient should expect will satisfy $v_{is}'(\widehat{m}_{is}) = q_s$.[7]

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[5] We could build a separate model of expected out-of-pocket spending that includes nonlinear cost sharing schedules, as in EMZ (2017), but as done in McGuire et al (2014) we use instead the plan's average cost share multiplied by the individual's expected spending on that service. We discuss below how we implement this empirically.
[6] That is $\bar{\mu}_i = max_{j \neq i} u_j(\widehat{m}_j)$.
[7] The explicit method of rationing used for different services is not specified in Glazer and McGuire, EM, or McGuire et al (2014) but deserves mention. We do not assume waiting time or inconvenience ("hassle factors") are necessarily worsened by plans that reduces the use of each service, which cause resource losses that deserve to be modeled. Rather we assume that the plan contracts with providers who are willing to provide fewer services of the types that the plan wishes to ration. As in Canada and much of Europe, it is not that most physicians have longer waiting times or less convenience, it is just that they tend to recommend and provide less intensive treatment for

We modify slightly the plan's objective function in McGuire et al (2014) and use

$$\pi(q) = \sum_i n_i(\widehat{m}_i(q))\pi_i$$
$$= \sum_i \left[\Phi\left(v_i(\widehat{m}_i(q)) - \bar{\mu}_i - \sum_s c_s \widehat{m}_i(q_s)\right)\right][rev_i - \sum_s (1-c_s) m_{is}(q_s)]$$

where $n_i(\widehat{m}_i) = \Phi\left(v_i(\widehat{m}_i(q)) - \bar{\mu}_i - \sum_s c_s \widehat{m}_i(q_s)\right)$ is the probability that health plan expects individual *i* would choose the plan; $\pi_i = rev_i - \sum_s (1-c_s) m_{is}(q_s)$ is the actual profit the plan receives for each individual where rev_i is the (possibly risk adjusted) revenue the plan receives for individual *i* and $\sum_s (1-c_s) m_{is}(q_s)$ is the health plan cost of covering individual *i* for using services covered by the plan given the structure of cost sharing.

This differs from the McGuire et al (2014) specification in that we assume that the demand for insurance takes into account that higher cost sharing reduces the probability that an individual will choose a health plan.

Applying the assumption of no cross-price effect, the derivative of profit with respect to q_s is:

$$\sum_i \frac{\partial}{\partial q_s}\{n_i(\widehat{m}_i(q))\pi_i\}$$

$$= \sum_i \frac{\partial}{\partial q_s}\{[\Phi_i(\sum_s(v_{is}(\widehat{m}_{is}) - c_s\widehat{m}_{is}) - \bar{\mu}_i)][rev_{i_i} - \sum_s(1-c_s)m_{is}(q_s)]\}$$

$$= \sum_i\{\Phi_i'(v_{is}'\widehat{m}_{is}' - c_s\widehat{m}_{is}')\pi_i - n_i(1-c_s)m_{is}'\}$$

Assume that the demand curve for insurance is locally linear, or equivalently the enrollment function is assumed to be locally uniform for all *i*, so that $\Phi_i' = \phi$. [8] Then we have,

$$= \sum_i\{\phi(v_{is}'\widehat{m}_{is}' - c_s\widehat{m}_{is}')\pi_i - n_i(1-c_s)m_{is}'\}$$

their patients. A good analogy is a school cafeteria serving free food to students, which can control the amount of each type of food (e.g., starch, protein, vegetables, salad, and dessert) offered to students without using prices, queues, or quality deterioration to control demand. This is what an efficient doctor/health care system should do.

[8] Although desirable to relax this assumption in future work, this strong assumption is used in FGM, EM, EJK, and Layton et al. (2017) which we continue here.

Plugging in $v_{is}^{'} = q_s$, we obtain,

$$= \sum_i \{\phi(q_s \hat{m}_{is}^{'} - c_s \hat{m}_{is}^{'})\pi_i - n_i(1-c_s)m_{is}^{'}\}$$

$$= \sum_i \{\phi\left(\left(\frac{q_s \hat{m}_{is}^{'}}{\hat{m}_{is}}\right)\hat{m}_{is} - c_s\left(\frac{q_s \hat{m}_{is}^{'}}{\hat{m}_{is}}\right)\frac{\hat{m}_{is}}{q_s}\right)\pi_i - n_i(1-c_s)\left(\frac{q_s m_{is}^{'}}{m_{is}}\right)\frac{m_{is}}{q_s}\}$$

The above expression includes terms that are elasticities of demand of actual spending and expected spending. Since we know of no literature in the health care area that tells us how the elasticity of actual spending differs from that of expected spending, we assume that they are the same, so that $\frac{q_s \hat{m}_{is}^{'}}{\hat{m}_{is}} = \frac{q_s m_{is}^{'}}{m_{is}} \equiv \eta_{is}$,[9] then the above can be rewritten as,

$$= \sum_i \{\phi\left(\eta_{is}\left(\hat{m}_{is} - c_s \frac{\hat{m}_{is}}{q_s}\right)\right)\pi_i - n_i(1-c_s)\eta_{is}\frac{m_{is}}{q_s}\} \qquad (3)$$

We assume that all individuals share the same elasticity of demand for each service but elasticities can differ across services, i.e., $\eta_{is} = \eta_s$.[10] Then we have,

$$\frac{\partial \pi(q)}{\partial q_s} = \eta_s \sum_i \{\phi\left(\hat{m}_{is} - c_s \frac{\hat{m}_{is}}{q_s}\right)\pi_i - n_i(1-c_s)\frac{m_{is}}{q_s}\}$$

Denote $\overline{m}_s$ as the average spending on service *s*, and *N* as the total number of people in the plan. This gives us $N\overline{m}_s = \sum_i n_i m_{is}$. Following EM and Frank, Glazer and McGuire (2000), we also calculate our metric at the value $q_s = 1$, which gives us:[11]

$$\frac{\partial \pi(q)}{\partial q_s} = \eta_s \sum_i \{\phi(\hat{m}_{is} - c_s \hat{m}_{is})\pi_i - n_i(1-c_s)m_{is}\}$$

$$= (1-c_s)\eta_s \sum_i \{\phi \hat{m}_{is}\pi_i - n_i m_{is}\} \qquad (4)$$

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[9] We allow individual expected spending to be different from the actual, but assume that their expectation is the same although actual individual spending can still have more noise.

[10] In the appendix, we extend the model to allow elasticities to be different across groups of consumers, such as young vs. old or sick vs. healthy.

[11] The choice of using $q_s = 1$ for calculating our selection elasticity is analogous to having to choose a price for calculating a specific demand elasticity. It does not imply that plans are necessarily all using this same shadow price to determine the quantity of services to provide. It just means that we are calculating all elasticities on the same point of the demand curve. If the health plan were a monopoly, or if every plan were receiving a capitated fixed premium, then each plan would prefer to choose a shadow price for each service such that the FSE would be equal to zero, so that profits could not be further increased.

The full selection elasticity (FSE) for service s, FSE_s, is the change in total profits (per dollar spent on a given health care service) with respect to the shadow price, q_s, written as:

$$FSE_s \equiv \frac{\partial\pi(q)}{\partial q_s} \times \frac{1}{N\overline{m}_s}$$

$$= (1 - c_s)\eta_s(\phi \sum_i \frac{\widehat{m}_{is}\pi_i}{N\overline{m}_s} - 1) \tag{5}$$

To convert the FSE_s expression to a function of a correlation and a standard deviation, define the correlation coefficient $\rho_{\widehat{m}_s,\pi} = \frac{\sum_i \widehat{m}_{is}\pi_i - N\overline{m}_s\overline{\pi}}{N\sigma_{\widehat{m}_s}\sigma_\pi}$ where $\overline{m}_s = \frac{\sum_i n_i\widehat{m}_{is}}{N}$ and $\overline{\pi} = \frac{\sum_i n_i\pi_i}{N}$, and let $\sigma_{\widehat{m}_s}$ and σ_π be the standard deviation of expected spending at the individual level and plan-level profits. We can then rewrite the full selection elasticity as:

$$FSE_s = (1 - c_s)\eta_s(\rho_{\widehat{m}_s,\pi}\phi \frac{\sigma_{\widehat{m}_s}\sigma_\pi}{\overline{m}_s} + \phi\overline{\pi} - 1) \tag{6}$$

The actual value of profits will not be observable in our data[12], since we do not have information about premiums and so in order to estimate equation (6), we define the average profit as a mark-up, δ, over average spending across all services, i.e., define $\overline{\pi} = \delta\overline{m}$:

$$FSE_s = (1 - c_s)\eta_s(\rho_{\widehat{m}_s,\pi}\phi \frac{\sigma_{\widehat{m}_s}\sigma_\pi}{\overline{m}_s} + \phi\delta\overline{m} - 1) \tag{7}$$

Note that expression (7) is a unit free measure consistent with the original definition of FSE_s as an elasticity. The formula contains seven terms. The two terms highlighted in EM are "predictability" $\frac{\sigma_{\hat{m}_s}}{\overline{m}_s}$, the coefficient of variation of the predicted spending on service s, and the "predictiveness" $\rho_{\hat{m}_s,\pi}$, which is the correlation between predicted service spending $\hat{m}_s$ and individual profit π. The five other terms are (1) $(1 - c_s)$, the fraction of the spending the insurer pays, (2) η_s, the demand elasticity for service s, (3) σ_π, the standard deviation of individual-level

[12] Note that because premiums do not change with individuals, we do not need their information to compute the standard deviation of profits, only the actual value.

profits, (4) ϕ, the density of distribution of individual specific valuation of health insurance, and (5) $\phi\delta\bar{m}$, the average profit, weighted by the density of distribution of individual specific valuation. These five terms were assumed to be constant across plan types and services in EM and EJK, so that they changed only the magnitude but not the order of rank in the selection index.[13] In this paper we relax this assumption and show that three of these terms not only affect the magnitude and the ranking of selection incentives but they also matter empirically by magnifying or mitigating how "predictability" and "predictiveness" shape selection incentives.

We draw attention to three terms in this expression affecting selection incentives that have not been previously analyzed. First, $(1 - c_s)$ captures that demand-side cost sharing reduces the attractiveness of supply-side rationing. Reassuringly, if individuals fully pay for the cost of care ($c_s = 1$), there is no incentive for a plan to undersupply that specific service.[14] Second, the demand elasticity can vary across services. For example, Duarte (2012) estimates price elasticities of demand for a few selected services in Chile, and finds greater price effect in services such as home visits ($\eta_s = -1.89$) and psychologist ($\eta_s = -2.08$), compared to services such as appendectomy ($\eta_s = -0.07$) or cholecystectomy ($\eta_s = -0.05$). Brot-Goldberg et al (2017) estimate that demand responses to increasing cost shares are larger for ER use, brand name pharmacy spending, than for inpatient hospital spending, mental health and prevention. Third, although the per-capita standard deviation of individual-level profits is constant for all services in a given payment system, it can change across alternative payment systems. Hence

[13] Not that both σ_π and ϕ interact with the predictability and predictiveness measures but not the constant 1. Hence they can affect the magnitude of the expression in parentheses, and the relative importance of selection across services by changing the sign of the expression in parentheses. In contrast the demand elasticities η_s only affect only the magnitudes, but not the relative importance of selection incentives.

[14] Conventional models of optimal insurance predict that higher cost sharing is optimal on services that are more demand elastic. Our result shows that tighter supply side shadow prices are also to be expected on more demand elastic services. Risk aversion and the cost of risk may mean that supply side service selection is still optimal even given some demand side cost sharing, as we find empirically below.

depending on the magnitudes of the first term inside the parentheses, it can potentially change both the magnitude and the ranking of the selection index.[15]

With relaxed assumptions, our FSE has an economic meaning - the change in profits given a unit increase in the shadow price as a fraction of total spending, and can be interpreted on its own. This is in contrast to the EM selection index that only estimates two terms and thus is only an ordinal term. In Section IV, we discuss in detail the empirical implementation of (7).

Expression (7) can be better understood in the following context. Consider services for which decreased spending is associated with increased profits and hence the covariance of profits with spending on these services is negative. But consumers do not base their enrollments on realized spending but rather on expected spending. Hence consumers use expected rather than actual spending on services to calculate this covariance. Since offering fewer services (by tighter rationing) deters enrollment, plans offer positive quantities of all services, but undersupply those with larger negative correlations with profits, which comes from a higher predictability and/or a more negative correlation with total spending. This incentive is also stronger when profits vary more across consumers, and for services where demand is more responsive to rationing, which is when demand elasticities are large.

III. Data

We use the Truven Analytic's MarketScan commercial claims and encounters data from 2008 to 2014. This large database contains service-level inpatient and outpatient medical claims, encounter records, prescription drug claims, enrollment and eligibility information from large employers, health plans, governments and public organizations. For this paper we used a sample of 73 employers with a specified health plan identifier. We focus on all individuals (both single

[15] Ellis, Jiang and Kuo (2013, footnote 10) perform an *ad hoc* correction for the standard deviation of profits in their calculation of a 56% reduction in selection incentives from prospective risk adjustment .We correct this imprecision here.

and family coverage) with at least three consecutive years of eligibility and claims information that include both pharmacy and mental health/substance abuse coverage. The first year of each person's claims and eligibility information are used to calculate lagged spending in each of 26 types of services.[16] We require that no individual changed plans during a calendar year, although we allow switches on January 1 of each year.

Our estimation sample contains 14 million person-years of information and is the same as that used in EMZ, to estimate demand elasticities for each of 26 categories of types of services. Further details about the data are summarized in EMZ. This sample is superior to the EJK data in that it enables us to compare incentives and behaviors over time, across broad health plan types, across single versus family coverage, and across specific employer-plans.

A key component of the full selection elasticity index is the predicted service-level spending, which we calculate by predicting year t service-level spending based on information from year t-1. Following EM and EJK, we use the information found to have the highest predictive power, namely prior year spending on each detailed type of service: in effect each consumer uses their own consumption vector on 26 types of services from year t-1 to predict their likely spending on each of those same services in year t. We discuss more details about estimation in Section IV. To select service categories for prediction, we started from the same categories used in EJK, but used a physician consultant (in internal medicine) to refine the analysis to a new set of 26 type of service categories. For each type of service we aggregate spending from detailed outpatient, inpatient and drug claims into their type of service categories for each enrollee. For spending we focus on the covered charge, a financial variable on claims that best approximates the medical resources used in treating patients. We discuss more details about this prediction strategy in Section IV.

[16] For people in 2008, information from 2007 was used to calculate lagged spending.

We examine five different health plan payment systems. One system is a risk adjustment model using age and gender only. For diagnosis-based risk adjustment, we use the prospective and concurrent DxCG relative risk scores from the Verisk Health hierarchical condition category (HCC) classification system (Ash et al., 2000), which is a richer, more predictive model than the one used in the US for Medicare payments to managed care plans and the ACA Health Insurance Marketplace risk adjustment. Finally, we examine two reinsurance programs calibrated to approximate the 2014 reinsurance program in the Marketplace, which reimbursed plans for 80 percent of costs above an attachment point of $60,000 per year, and hence we call the 80% after $60k government reinsurance system. We implicitly adjust the premiums paid to reflect the payout of this reinsurance, without adding any administrative costs, and examine it both with and without concurrent risk adjustment.

IV. Estimation Strategy

To obtain the full selection elasticity (FSE) index for each service s in expression (7), we need to separately calculate predictability and predictiveness as in EM and EJK, which requires predicting service-level spending for the prediction year t using information from the prior year, t-1. We discuss this in more detail below. For c_s, the ideal cost share to use would be the plan's expected share of costs of each service that it bears, which depends on the plan's price schedule and consumers' anticipation of relevant cost shares when choosing health plans *ex ante*. Absent information about plan pricing schedule in our data and without a model of consumer plan choice, we instead use the plan's average actual cost share for each service.[17] The demand elasticities for service s, η_s, use new results from EMZ that uses the same sample and service

[17] It is straightforward to examine how changes in cost sharing rates would affect the FSE, such as the changes in going from gold to silver Marketplace plans, however we show empirically that the effects on our elasticities are negligible.

categorization as ours. The standard deviation of ex-post profits across individuals, σ_π, can be readily calculated from the data.[18] We also need an estimate of ϕ which we discuss below. Finally, the term $\phi\delta\bar{m}$ depends on the value of the mark-up, δ, assumed. Nevertheless, when weighted by the density of the individual valuation, this term is very close to zero, in such a way that the assumption made on the mark-up affects the final estimates only marginally. Throughout the paper, we assume $\delta = 0.2$, meaning that insurers have a mark-up of 20% over all spending. We view this as an upper bound on the actual mark-up, but our estimates are not sensitive to this choice.[19] Below we further discuss the estimation of key components in FSE.

To obtain predicted service-level spending, we use linear predictive model specifications. There may be concerns that ordinary least squares model (OLS) may not appropriately capture classical features of health expenditures such as a large proportion of zero expenditures and a long right trail, and more advanced econometric methods should be used. Several recent studies (EM, 2007, and Dusheiko et. al., 2009) have shown that with very large samples, OLS performs about as well as more advanced econometric specifications at recovering predicted subsample means. Both EM and EJK tested the sensitivity of their estimates of selection index to alternative nonlinear specifications and found them to be quite robust. For this paper, we focus on simple OLS results.

In terms of information set used for predictions, we followed EM and EJK, and tested several combinations of variables that could potentially predict spending in the subsequent year. All specifications included age-gender dummy variables as well as further information. The explanatory variables included were prior year total covered charges, HCC diagnosis-based

[18] We extend the discussion of FGM, EM, EJK, and Layton et al (2017) by allowing for nonzero profit plan payment systems.

[19] In fact, going from the zero profit condition, where $\delta = 0$ to a 0.2 mark-up changes our estimates only on the second decimal place, and not for all types of services.

dummies (based on Ash et al, 2000), and prior year service-level spending decomposed by type of service. Similar to EM, we find the most predictive information set to use for predicting spending by type of services is disaggregated spending by type of service the preceding year. Specifically, we estimate a model of the following form.

$$m_{s,t} = f(age, gender, m_{1,t-1}, \dots, m_{26,t-1})$$

For service-level demand elasticities, we rely on new elasticity estimates from EMZ that uses a new instrumental variables approach exploiting within-year variation in cost shares to estimate demand sensitivity for each service. Their IV estimator takes advantage of the significant deductibles and stoplosses in some, but not all health plans, in the large MarketScan data from 2008 to 2014, and uses individual-year fixed effects to calculate the differential demand response of individuals facing high or low cost shares during a given calendar year. In effect, their estimator is using differences in consumption early in the year and at the end of the year among individuals whose costs shares decline within the year. The authors overcome the endogeneity between spending and cost share using a novel instrumental variable technique, which is possible because they have 73 employers spanning multiple year, each offering multiple health plans. Specifically, they use the average cost share of other individuals in the same plan and month as an instrument for individual cost shares. This instrument is attractive since other individuals' cost shares correlate with the individual's cost share as all individuals are subject to the same plan characteristics (cost shares, deductibles and stoplosses), but are uncorrelated with the individual's spending. Previous studies using nonlinear plan features have not had this plan-year level instrument available since they have only used a single employer or a few health plans.

To estimate demand elasticities, EMZ use a log-linear specification where the outcome variable is the log of 1/12 plus individual spending on a particular type of service. Although they estimate two-part models, they choose this specification as their preferred one because it reduces model sensitivity to long tails in spending and allows for a direct estimation of overall demand elasticity. For this paper, we use EMZ results based on backward myopic price expectations of consumers, in which decisions on care seeking and intensity for each service are based on the beginning of the month cost share, rather than the end of the month cost share or expected end-of-the-year cost share. These monthly cost shares are instrumented by the average actual cost shares of other plan enrollees in that same month, so measurement error in this price are presumably at least partially controlled for by this IV estimation.[20]

One advantage of EMZ is that their identification strategy does not rely on plan-type variation in cost sharing, but rather within-year variation. The main concern about their IV strategy is that elasticity estimates will be biased if consumers who are more demand sensitive are more willing to enroll in plans with higher cost sharing, as found by Einav et al (2013) and Brot-Goldberg et al (2017). EMZ address this concern by estimating demand responsiveness separately for three plan types (PPO, HMO, and HDHP) and confirm the previous finding. EMZ calculate that the overall elasticity of demand is -1.39 for HDHP versus -1.49 for HMOs and -1.17 for PPOs, and they find even larger differences for outpatient services and pharmaceuticals. We revisit this issue below, where we also conduct a sensitivity analysis to estimate service elasticities by plan type, as well as by patient age, year, risk scores, and family/single coverage.

One disadvantage of the EMZ identification strategy is that it is unable to estimate elasticities with adequate precision for services that almost invariably bring the cost sharing to

[20] EMZ also generate demand elasticities for forward myopic prices, using the end of the month cost shares (again instrumented by actual spending) and get very similar results.

zero, because such spending will exceed plan deductibles or stoplosses. Most hospice spending, room and board fees, and major surgeries do this, so the technique is not well suited for generating elasticities for these services.

One empirical challenge of calculating (7) is to estimate ϕ, the average change in the probability of choosing a health plan for an additional dollar of expected spending. Estimating this parameter is beyond this paper. Instead, we use the following "back of the envelope" logic to come up with a reasonable approximation, and then perform sensitivity analysis on our estimated results to alternative values. A recent systematic review of the elasticity of demand for health insurance by Pendzialek et al (2016) finds a range of -0.2 to -1.0 for the US, with a midpoint of -0.6 which we use here. Based on other recent research, consumers seem to be much more responsive to premiums, which are very salient, than to the extent of coverage, which is harder to observe. We assume that consumers are only half as responsive to expected spending changes as premiums, suggesting that the elasticity of plan choice to expected spending is plausibly 0.3. To convert this into a slope, we multiply by the mean plan market share of the plans among all employers' offerings in our sample (0.238) and divide by the average total spending which is \$4,354. Combining these yields 1.64×10^{-5} as our point estimate for ϕ, meaning that increasing expected spending on medical care by \$1,000 increases the market share of a plan by 0.0164, which is about 7% of its mean. We also conduct sensitivity analysis using 0.5ϕ and 2ϕ which bound likely values, or at least is informative about the sensitivity of the ranking to this unknown parameter.

In order to understand the consequences of risk adjustment, we recalculate the full selection elasticities under four risk adjustment scenarios: no risk adjustment, age and gender risk adjustment, prospective diagnosis-based risk adjustment, and concurrent diagnosis-based risk adjustment. We also contrast risk adjustment with a simple reinsurance program in the absence of any risk adjustment and a combination of reinsurance and concurrent risk adjustment.

V. Empirical Results

A. *Descriptive Statistics*

Table 1 provides summary statistics for our sample, showing means and standard deviations of plan type market shares, age, and current and prior year total spending. We focus on four plan types that are popular and of particular policy interest: HMO, PPO, CDHP and HDHP. The final column shows mean consumer cost shares by plan type, revealing that HMOs and comprehensive plans have notably lower average cost shares than CDHPs and HDHPs, as expected.

B. *Selection Incentives by Type of Service and Risk Adjustment*

Table 2 summarizes the basic components of the full selection elasticities for 26 type-of-service categories for our full sample under the assumption that there is no risk adjustment.[21] The two parameters that are constant for the calculation in this table are the standard deviation of individual profits σ_π which is calculated as 58,243 with no risk adjustment, and the insurance demand responsiveness parameter, which is $\phi = 1.64 \times 10^{-5}$ for our base case. The first two columns shows mean spending and cost share on each detailed service, while columns (3) through (5) show the demand elasticity η_s from EMZ, the predictability (CV), and the Predictiveness ($\rho_{\hat{m}_s,\pi}$), respectively. The final two columns show two selection incentive measures. Column (6) uses the EM definition of its selection index, which is the product of only the predictiveness and predictability terms. Column (7) calculates the selection incentives using all six terms as we have developed above for our full selection elasticity (FSE). One important

[21] Estimates of detailed components presented in Table A-1.

advantage of our FSE is that it has an explicit interpretation: it is the elasticity of average profits per person with respect to rationing spending on that service by one more percentage point, as defined by equation (7). The elasticity on overall spending suggests that raising the shadow price of all medical services by one percent will raise average profits by 1.60 percent, with considerable variation across services.

Table 2 results show several interesting patterns. First, the EM index, which does not depend on any estimates of demand elasticity or other constants, finds that the services most vulnerable to underprovision are home visits[22], dialysis and PET scans. The demand elasticities of dialysis and surgical procedures are imprecisely estimated and of the wrong sign. While it is credible that these would be some of the favorite services for plans to heavily discriminate against and underprovide, we are not able to estimate our new FSE for these services since the demand elasticities (shown in the first column) are implausible, and we therefore omit these two services from the rest of our main analysis.[23]

Second, both the EM and the new FSE metric identify pharmacy spending (FSE=1.80) as very prone to use for selection, with inpatient (FSE=1.11) and PET scans (FSE=1.29) also having high incentives for selection. On the other extreme, prevention (FSE=0.02), ER (FSE=0.07) and maternity (FSE=0.09) have extremely low elasticities. Demand elasticities are sufficiently low for home visits and ambulances that even though they have sizable incentives to select using the EM selection index, in our new FSE metric, they have low selection elasticities.[24]

[22] Home visits are very rare in our sample of the privately insured, and mostly reflect follow up care for very sick people following inpatient care, which appears to be very inelastically demanded.
[23] Results for these services are presented in the Appendix A.
[24] We also found (results not shown) that including $(1 - c_s)$ changes the magnitude but not the ranking of the incentives to select for the majority of our types of services.

Table 3 recalculates our full selection elasticity for six payment systems on overall spending and the 24 (out of 26) services with plausible demand elasticities. The first column replicates the final column of Table 2, which corresponds to no risk adjustment. In our base case, the standard deviation of individual profits is 58,243. Column (2) implements age-sex risk adjustment, which also can be seen as capturing incentives of variable premium plans when premiums are allowed to vary by age and sex categories, so that profits are exactly zero, not only in aggregate, but also for each age-sex group. We see here that age sex adjustment has only a modest effect on incentives, lowering the elasticity for all spending only from 1.6 to 1.51.

Column (3) implements prospective diagnosis-based (DX) risk adjustment using prospective relative risk score (RRS), while column (4) presents the results using the concurrent relative risk score. The prospective risk adjustment system is similar to the risk adjustment that underlies the Medicare Advantage risk adjustment approach, while the concurrent model is similar to the formula used in the Health Insurance Marketplace, although the DxCG classification system is richer and more predictive than the systems used in these two public programs. Columns (3) and (4) show that selection incentives are reduced meaningfully by both forms of risk adjustment, with prospective risk adjustment showing a 43 percent reduction (1-0.92/1.6) in incentives to select, while concurrent risk adjustment achieves a 47 percent reduction (1-0.85/1.6) for all spending. Table A-2 shows the detailed results of selection incentive components with risk adjustment.

The fifth column in Table 3 examines the impact of a reinsurance program that approximates the program in place for the 2014 Marketplace reinsurance system which compensated plans for 80% of spending after exceeding $60k. As expected, the reinsurance programs are highly effective at reducing the overall variability of profits. Column (5) shows that a simple reinsurance program without risk adjustment reduces the standard deviation of individual profits to $32,293 which is an impressive 45 percent reduction from the no risk adjustment levels. However, the selection elasticity for all spending is 1.09, which is only a 32 percent reduction relative to the base case. Simple reinsurance is less successful at reducing selection incentives than either risk adjustment model.

The superiority of risk adjustment over simple reinsurance in our results was a surprise to us. Why is this? Not shown in Table 3, but presented in appendix Tables A-3 is the fact that reducing the spending in the upper tail improves the correlation of expected spending on most services with the (partially) truncated actual profit. Expected spending on many types of services are more weakly correlated with total spending (and hence non-risk adjusted profits) than they are with spending after reducing the size of the upper tail. This improvement is sufficiently large that for our model of consumer expectations, the increased predictiveness outweighs the reduced standard deviation of profitability.[25]

The final column of Table 3 shows a combination of the reinsurance program with concurrent risk adjustment. Under this program, the standard deviation of individual profits is reduced by 62% of the initial value. However, the increase in predictiveness over risk adjustment models is modest, and overall selection incentives decrease compared to any other model, from 1.6 in the base case to 0.64, a 60 percent reduction from the base case and a 24 percentage reduction from concurrent risk adjustment without reinsurance. Figure 1 summarizes our FSE results for each type of service, under six payment scenarios. Here the patterns across services and different forms of reinsurance are visible, as well as the modest superiority of concurrent risk adjustment over prospective, and the weaker performance of simple reinsurance. This graphical

[25] Note that predictability is left unchanged in our formulation, since expectations about spending on a particular service are unaffected by the reinsurance program. We did not do any topcoding on spending by TOS, which would be another direction to explore.

presentation also makes it easier to see how strong the incentives are to use availability of pharmaceuticals to influence selection, versus using either prevention or maternity services.

C. Selection Incentives by Specified Subgroups of the Full Sample

We next compare our FSE measure of selection incentives among various subsets of our full sample. Estimates for each subgroup were generated by recalculating four of the six components of the selection elasticities shown in Equation (7). Hence, for each service and for each subgroup, we used the same model of expectations for each subsample, but separately recalculated the average cost share, its predictability, predictiveness and profit variation. We use the same set of demand elasticity estimates for each calculation, since such elasticities were not computed at the service level for all groups in EMZ, as well as the responsiveness parameter (ϕ). Because demand elasticities have a multiplicative impact on our index, the bias in our estimates due to the use of overall elasticities for each service, not group-specific values, can be easily evaluated. For example, EMZ calculate that the demand elasticity for the highest risk score individuals is 34% lower than for low risk score individuals. So, on average our FSE, for the former group is overestimated by 34%. EMZ also confirm the findings of Einav et al (2013) and Brot-Goldberg et al (2017) that elasticities are higher in HDHPs than in low deductible plans such as HMOs, although they do not estimate elasticities for the full set of services examined here. We find these subgroups interesting because health plans and the employers who contract with them often get to design plan features across these subgroups. At the most basic level, plans get to change designs across plan type and years, for instance, and premiums are allowed to vary by age group and single versus family coverage. Plans are generally not allowed to differentiate premiums across enrollees by risk scores, but the results are nonetheless interesting to confirm that if plans were allowed to do so, there would be much more profit to distort services among those with high risk scores than with anyone else. Confirming the results in EJK we show in the appendix that the selection measures are highly stable across subsets of the total population with most correlations above 0.93.

The first set of bars in Figure 2 summarize the weighted average FSE for our six different plan types shown at the top of Table 4. Sample sizes are adequate for each simulation: Table 1 shows that even our least common plan type (Comprehensive) still has information on 216,409 people. Here, as in Ellis and Zhu (2016), we present plan types in the order of those that emphasize supply side incentives the most to those that rely on demand side incentives to control costs. The full selection elasticities are modestly lower both for plan types that rely on supply side incentives such as HMOs and POS, and for plan types such as HDHPs that rely on demand side incentives. HDHPs have a full selection elasticity (1.37) that is comparable to HMOs (1.32), despite their very different selection approaches.[26]

The next two segments of Figure 2 (derived from Appendix Table A-4) examine whether selection incentives vary over time, and between single and family contracts. Even though we deflated spending by the personal consumption expenditure deflator for health care, there is still some evidence that incentives to select are growing over our sample period, between 2008 and 2014. The overall incentive to select is similar in family and single coverage plans, even though only the former contain young children.[27]

The next segment of Figure 2 (based on Appendix Table A-5) shows the results by age group. The results show stronger incentives to select against the old than against the younger adults, but surprisingly strong incentives to select against children aged 0 to 20. Note that

[26] Interestingly, we also found (results not shown) that taking into account $(1 - c_s)$ in our calculation dampens selection incentives in plan types that rely more on cost sharing to control costs (i.e., CDHP, HDHP) relative to other plan types, but the adjustment does not change the ranking of this incentive across plan types.
[27] Note that throughout this paper we are modeling individual rather than contract level selection incentives. We did not model the effects of pooling multiple people in family contracts.

implicit in these calculations is the idea that premiums vary such that average profits are zero for each of these four age groups, so it is variability in profits within each group that are driving the results. Two detailed results are of interest. Pharmacy remains one of the strongest categories with incentives to distort, while prevention and ER visits appear attractive to provide generously across all age groups. The selection elasticities for the youngest age group are only correlated with overall selection at ρ=0.743, which is the lowest correlation of any subgroup evaluated.

The last set of results in Figure 2 (with details in Appendix Table A-5) show our weighted average FSE by intervals of prospective relative risk scores (RRS). Note that we did not use any risk adjustment in any of the calculations in this figure, so these numbers reflect the incentive to select among people with low, medium high and very high expected costs. It is no surprise that incentives to select grow enormously across risk scores, with FSE that are more than five times higher on average for very high RRS categories. The final row of table A-5 shows that the calculated risk scores remain moderately correlated for lower RRS individuals.

We examined time trends in FSE not only for the no risk adjustment base case shown here, but also for each of the other payment systems. As shown in the appendix Figure A-1, payment systems that use reinsurance seem to grow more slowly than other alternatives.[28]

D. *Sensitivity analysis to alternative values of* ϕ

As discussed in our estimation strategy section, the one parameter that we are unable to estimate in our data is ϕ, the derivative of the probability of choosing a plan with respect to expected spending. Here, we examine the sensitivity of our selection elasticity results to alternative values of ϕ, both for the no risk adjustment case and the concurrent risk adjustment case. Results are presented in Table A-6. The elasticities vary with ϕ, changing nearly

[28] Our constant ϕ, represents the derivative of the probability of joining a health plan with regard to spending one more dollar on medical care, and hence uses nominal dollars. If there is inflation or changes in preferences, this would change this number and our FSE. Hence trends over time that do not control for this may not be meaningful.

proportionately when ϕ is doubled or halved. The full selection elasticities remain highly correlated as this parameter is changed, with correlations above 0.95. This stability might disappear if we estimated ϕ specific to each service, but if all expected spending on all services affect enrollment in the same way, then our results are not sensitive to this parameter.

VI. Conclusion

This paper applies the methodology proposed by Ellis and McGuire (2007) and refined by McGuire et al (2014) to a large commercial insurance dataset for the period 2008-2014. We confirm the EM finding that selection incentives are strong for services commonly thought to be provided more by non-managed care than managed care commercial plans. We also introduce new refinements in the assessment of service-level incentives that are missed in previous studies. In particular, incorporating service-level demand elasticities meaningfully changes our conclusion about selection incentives of some services. We find that services such as home visits and ambulance spending, while predictive of total profits, are so inelastically demanded that there is little incentive to distort them for selection.

Interestingly, risk adjustment is more effective at reducing selection incentives than simple reinsurance. This finding reflects that while reinsurance does reduce the variability of profits, it also improves the predictiveness of the uninsured spending, making service selection more effective at changing profitability. Using a combination of reinsurance and risk adjustment, we can take advantage of both a lower variability in profits and lower predictiveness, resulting in lower selection incentives in all our models.

One important weakness of our analysis is that we are unable to estimate, and hence to incorporate, the effects of variations in insurance demand responsiveness to changes in expected spending. While we do estimate η_s, demand elasticity for each type of service, we do not yet have service-specific estimates of ϕ, how increased availability of service s affects the probability of joining a health plan. It remains to potentially estimate health plan demand models to see how spending by type of service affects plan choices.

This paper introduces a number of refinements to the calculation of selection indices that reflects new empirical estimates – of service-level demand elasticities, sensitivity of health plan choice to increased medical spending, profit margins, and assumptions about how service-level cost sharing affects demand. Future studies will be needed to refine these estimates - in particular how various price elasticities are estimated – in order to further move this literature forward.

We are also aware that our selection elasticity is only a partial measurement of selection strategies used by insurance plans. Other than service-level distortion focused in this paper, private insurers could directly advertise their plans to the targeted population; or they select favorable enrollees through benefit plan design; or they dump those undesired potentially high cost individuals. Our FSE would not capture those regulated services. But the metric still characterizes the subtle incentives to ration services by insurers. Market competitiveness could potentially also affect selection incentives, which we ignore.

Despite the caveats, this study can help improve health plan payment policy. Our findings show that concurrent risk adjustment reduces selection incentives meaningfully, by as much as 47%, and a combination of risk adjustment and reinsurance reduces the incentive by 60%. The services identified as prone to be distorted are important for policy makers to monitor so as to neutralize commercial plans' incentives. The results have implications for managed care regulation, capitation formula, employment-based insurance, provider payment, and health system research.

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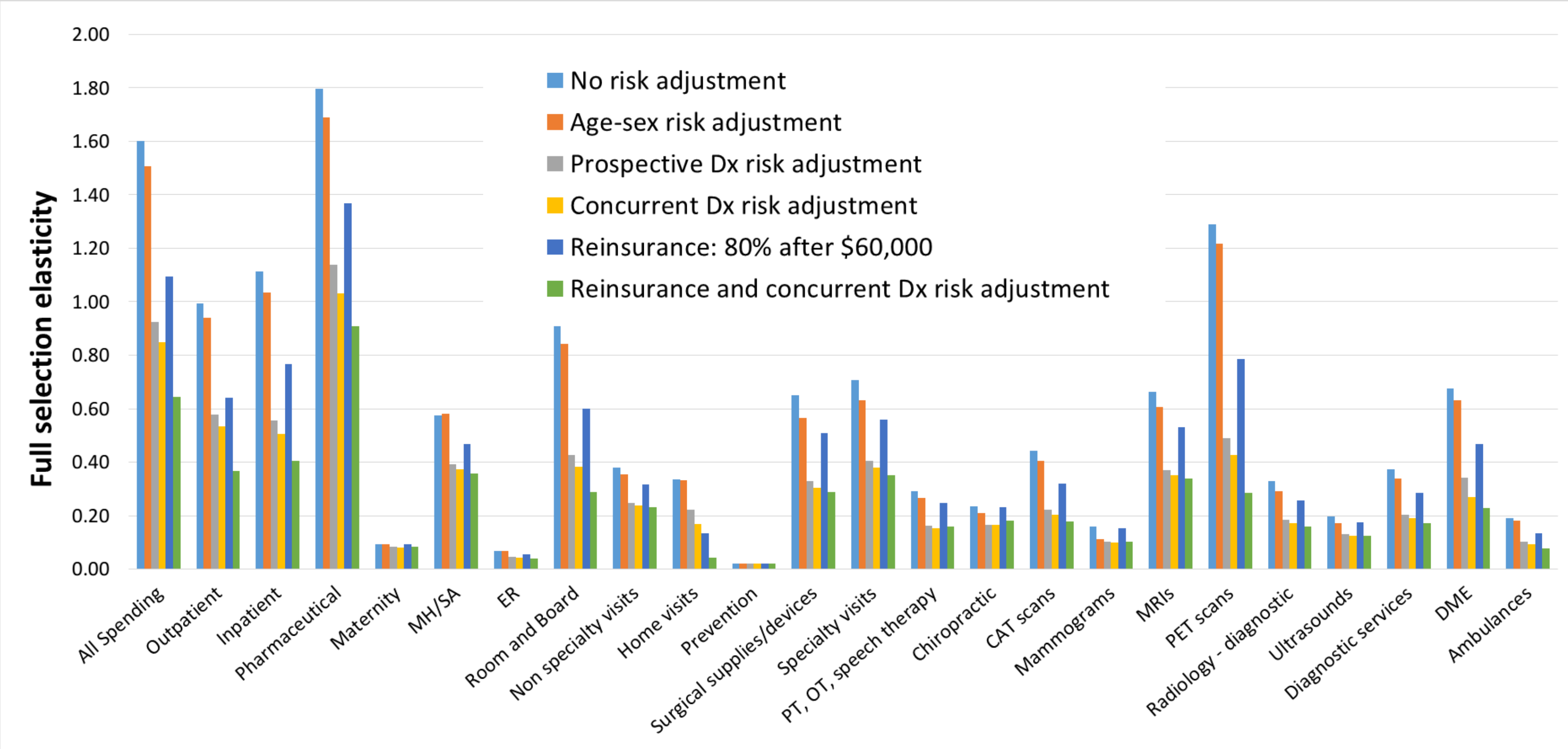
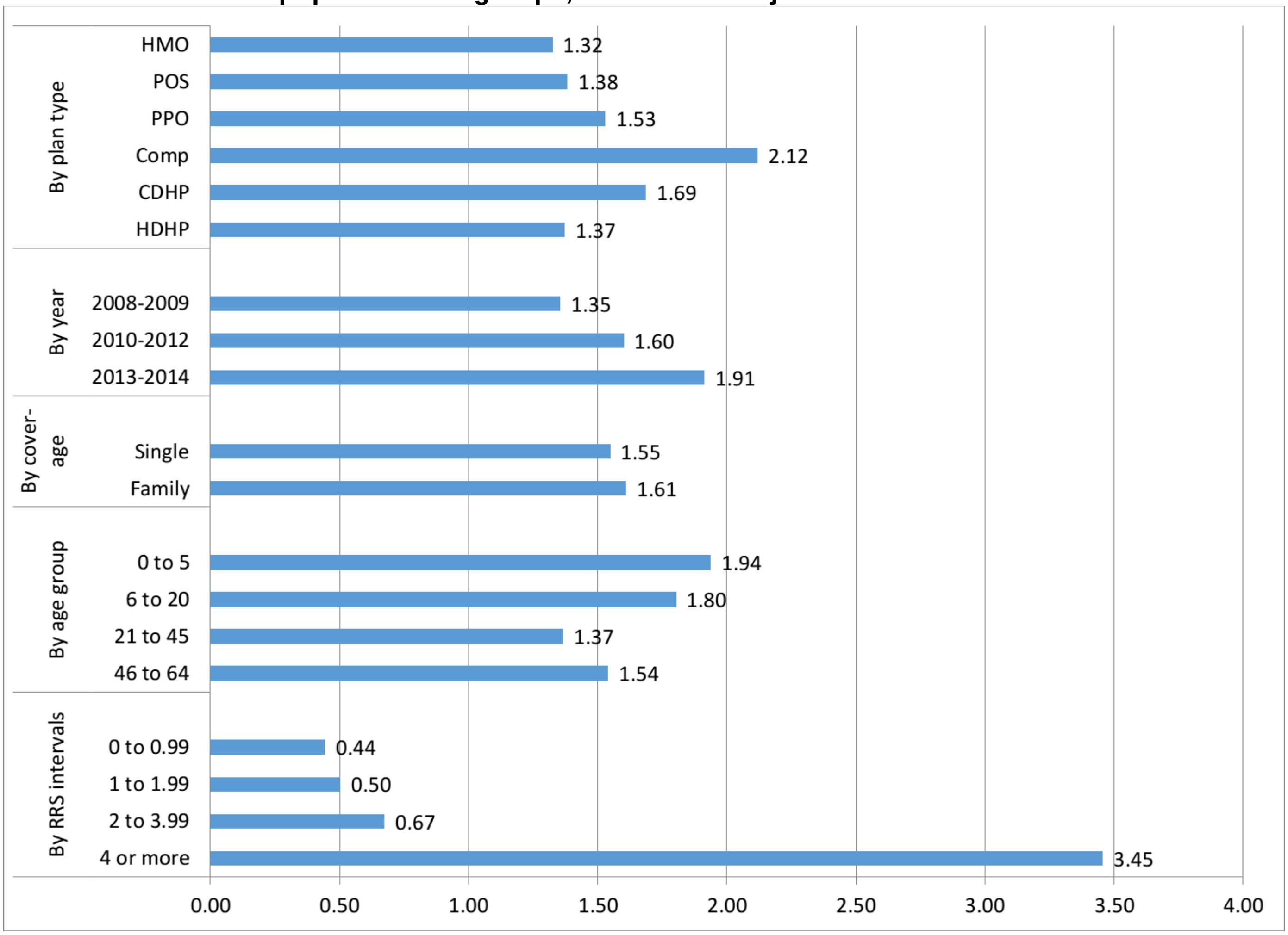
Figure 1 – Full selection elasticity results



Notes: The FSE for two services (surgical procedures and dialysis) are not reported, as the elasticities for these services likely are not well-identified (wrong sign).

Figure 2 – **Comparison of the full selection elasticity (FSE) for all spending across population subgroups, with no risk adjustment**



Notes: Each bar presents FSE of all spending recalculated for each population subgroup, as presented in appendix Tables A-4 to A-6. The FSE was recalculated separately for each population subgroup, which implicitly allows premiums to adjust so that profits are zero on average for each calculation. This is plausible for plan type, year, coverage category, and age group, but implausible for RRS intervals. See text for discussion.

Table 1 – Basic statistics by plan types

	N	Age		Current year total spending		Prior year total spending		Mean cost share
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Full sample	13,902,952	34.0	18.3	4,354	16,813	3,942	14,246	0.13
By Plan type:								
HMO	2,486,259	30.7	17.7	2,757	13,792	2,507	12,295	0.07
POS	1,491,322	34.1	17.8	4,233	15,641	3,823	13,154	0.14
PPO	8,305,156	35.0	18.5	4,869	17,724	4,407	14,937	0.13
Comprehensive	216,409	42.2	18.8	6,300	21,079	5,775	18,342	0.11
CDHP	1,162,945	32.9	17.9	4,018	16,594	3,615	13,588	0.19
HDHP	240,861	32.5	18.1	3,693	15,445	3,348	12,787	0.25

Notes: Results are based on the Ellis, Martins and Zhu (2017) sample of 13,902,952 people, ages 0 to 64, in large, privately insured plans, including both single and family coverage, with at least three consecutive years of 12 months of eligibility, with no switching among different plans during a calendar year. Mean sost share is defined as the sum of out-of-pocket spending divided by the sum of total spending.

Table 2 – Selection incentive components for 26 types of service with no risk adjustment

	Mean spending	Mean cost share	Elasticity	CV	$\rho_{\widehat{m}_s,\pi}$	EM selection index	Full selection elasticity
All Spending	4,353.78	0.13	-0.44 ***	6.71	-0.50	-3.37	1.60
Outpatient	2,478.42	0.15	-0.29 ***	7.19	-0.45	-3.22	0.99
Inpatient	916.57	0.05	-0.30 ***	7.60	-0.40	-3.08	1.11
Pharmaceutical	958.90	0.16	-0.44 ***	12.02	-0.33	-4.02	1.80
Maternity	133.83	0.11	-0.09 *	8.77	-0.03	-0.23	0.09
MH/SA	124.12	0.19	-0.26 ***	17.78	-0.10	-1.80	0.57
ER	220.00	0.17	-0.04 *	4.64	-0.25	-1.14	0.07
Room and Board	375.05	0.03	-0.20 **	10.68	-0.36	-3.84	0.91
Non specialty visits	293.16	0.22	-0.25 ***	3.23	-0.30	-0.98	0.38
Home visits	11.51	0.04	-0.01	274.11	-0.11	-29.90	0.34
Prevention	50.42	0.04	-0.02 *	2.48	-0.03	-0.08	0.02
Surgical procedures	86.52	0.02	0.07	7.12	-0.36	-2.57	-0.24
Surgical supplies/devices	56.42	0.02	-0.22 **	6.63	-0.32	-2.09	0.65
Specialty visits	708.33	0.15	-0.32 ***	4.75	-0.35	-1.67	0.71
Dialysis	30.29	0.03	0.02	205.99	-0.19	-39.37	-0.87
PT, OT, speech therapy	98.70	0.20	-0.15 ***	8.60	-0.18	-1.51	0.29
Chiropractic	25.75	0.34	-0.23 ***	12.79	-0.05	-0.62	0.24
CAT scans	62.53	0.13	-0.15 ***	8.28	-0.31	-2.53	0.44
Mammograms	31.29	0.07	-0.11 ***	6.80	-0.10	-0.68	0.16
MRIs	73.61	0.16	-0.29 ***	6.13	-0.30	-1.81	0.66
PET scans	6.51	0.06	-0.17 *	44.33	-0.16	-7.22	1.29
Radiology - diagnostic	71.53	0.17	-0.15 ***	4.28	-0.39	-1.67	0.33
Ultrasounds	32.24	0.21	-0.14 ***	4.23	-0.20	-0.85	0.20
Diagnostic services	116.88	0.13	-0.15 ***	5.26	-0.38	-1.99	0.37
DME	27.36	0.15	-0.18 ***	15.81	-0.23	-3.57	0.68
Ambulances	23.98	0.10	-0.07	7.57	-0.31	-2.36	0.19
ϕ = derivative of the probability of choosing a plan with respect to expected spending							1.64E-05
σ_π = standard deviation of individual profit							58,243
δ = spending mark-up							0.20

Notes: Results shown assume no risk adjustment and estimate the five components of the full selection elasticity as discussed in the text. Results use the full sample of 13,902,952 single and family enrollees, 2008-14 in 73 identified employers, for a sample of enrollees continuously eligible for at least three full calendar years with no mid-year plan switching.

Table 3 – Comparison of full selection elasticities for four risk adjustment models and two reinsurance models

	No risk adjustment	Age-sex risk adjustment	Prospective Dx risk adjustment	Concurrent Dx risk adjustment	Reinsurance: 80% after \$60,000	Reinsurance and concurrent Dx risk adjustment
All Spending	1.60	1.51	0.92	0.85	1.09	0.64
Outpatient	0.99	0.94	0.58	0.53	0.64	0.37
Inpatient	1.11	1.04	0.56	0.51	0.77	0.40
Pharmaceutical	1.80	1.69	1.14	1.03	1.37	0.91
Maternity	0.09	0.09	0.08	0.08	0.09	0.08
MH/SA	0.57	0.58	0.39	0.37	0.47	0.36
ER	0.07	0.07	0.05	0.04	0.06	0.04
Room and Board	0.91	0.84	0.43	0.38	0.60	0.29
Non specialty visits	0.38	0.35	0.25	0.24	0.32	0.23
Home visits	0.34	0.33	0.22	0.17	0.14	0.04
Prevention	0.02	0.02	0.02	0.02	0.02	0.02
Surgical supplies/devices	0.65	0.57	0.33	0.31	0.51	0.29
Specialty visits	0.71	0.63	0.40	0.38	0.56	0.35
PT, OT, speech therapy	0.29	0.27	0.16	0.15	0.25	0.16
Chiropractic	0.24	0.21	0.17	0.17	0.23	0.18
CAT scans	0.44	0.41	0.22	0.20	0.32	0.18
Mammograms	0.16	0.11	0.10	0.10	0.15	0.10
MRIs	0.66	0.61	0.37	0.35	0.53	0.34
PET scans	1.29	1.22	0.49	0.43	0.79	0.28
Radiology - diagnostic	0.33	0.29	0.18	0.17	0.26	0.16
Ultrasounds	0.20	0.17	0.13	0.13	0.18	0.13
Diagnostic services	0.37	0.34	0.20	0.19	0.28	0.17
DME	0.68	0.63	0.34	0.27	0.47	0.23
Ambulances	0.19	0.18	0.10	0.09	0.13	0.08
ϕ = derivative of the probability of choosing a plan with respect to expected spending	1.64E-05	1.64E-05	1.64E-05	1.64E-05	1.64E-05	1.64E-05
σ_π = standard deviation of individual profit	58,243	57,669	52,946	40,898	32,293	21,906
δ = spending mark-up	0.2	0.2	0.2	0.2	0.2	0.2
Correlation with base case	1	0.999	0.971	0.964	0.988	0.916

Notes: Results use the full sample of single and family enrollees, 2008-14 in 73 identified employers, for a sample of 13,902,952 enrollees continuously eligible for at least three full calendar years with no mid-year plan switching. Not shown are results for two services with insignificant or wrong sign demand elasticities.

Table 4 – Comparison of full selection elasticities across subgroups: by plan type, without risk adjustment

	Plan Type					
	HMO	POS	PPO	Comp	CDHP	HDHP
All Spending	1.32	1.38	1.64	2.12	1.69	1.37
Outpatient	0.83	0.89	1.00	1.54	1.10	0.74
Inpatient	0.94	1.03	1.15	1.22	1.16	1.20
Pharmaceutical	1.43	1.34	1.90	1.89	1.71	1.82
Maternity	0.11	0.08	0.09	0.08	0.09	0.08
MH/SA	0.49	0.58	0.56	0.62	0.67	0.82
ER	0.06	0.07	0.07	0.10	0.06	0.05
Room and Board	0.73	0.86	0.95	1.10	0.88	0.78
Non specialty visits	0.43	0.36	0.37	0.53	0.34	0.22
Home visits	0.26	0.39	0.27	0.90	0.49	0.20
Prevention	0.02	0.02	0.02	0.02	0.02	0.02
Surgical supplies/devices	0.59	0.63	0.65	0.63	0.66	0.66
Specialty visits	0.70	0.78	0.70	0.87	0.62	0.56
PT, OT, speech therapy	0.29	0.28	0.29	0.43	0.28	0.22
Chiropractic	0.20	0.16	0.24	0.30	0.19	0.16
CAT scans	0.38	0.44	0.44	0.51	0.44	0.48
Mammograms	0.17	0.16	0.16	0.16	0.16	0.14
MRIs	0.65	0.65	0.66	0.81	0.57	0.58
PET scans	1.03	1.24	1.32	1.20	1.34	1.37
Radiology - diagnostic	0.33	0.32	0.32	0.46	0.30	0.26
Ultrasounds	0.22	0.20	0.20	0.22	0.16	0.13
Diagnostic services	0.38	0.37	0.37	0.38	0.36	0.34
DME	0.65	0.68	0.65	1.25	0.71	0.51
Ambulances	0.14	0.16	0.20	0.37	0.21	0.12
σ_π = standard deviation of individual profit	47,776	54,182	61,398	73,024	57,482	53,502
δ = spending mark-up	0.2	0.2	0.2	0.2	0.2	0.2
Correlation with base case	0.994	0.985	0.999	0.944	0.992	0.975

APPENDIX A

Table A-1 – Detailed results of selection incentive components by type of service with no risk adjustment

	Elasticity	Mean spending	Std. dev.	R^2	C.V.	No risk adjustment $\rho_{\hat{m}_s,\pi}$	No risk adjustment EM selection index	No risk adjustment Full selection elasticity
All Spending	-0.44	4,354	29,223	0.25	6.71	-0.50	-3.37	1.60
Outpatient	-0.29	2,478	17,819	0.32	7.19	-0.45	-3.22	0.99
Inpatient	-0.30	917	6,962	0.04	7.60	-0.40	-3.08	1.11
Pharmaceutical	-0.44	959	11,526	0.60	12.02	-0.33	-4.02	1.80
Maternity	-0.09	134	1,174	0.04	8.77	-0.03	-0.23	0.09
MH/SA	-0.26	124	2,207	0.14	17.78	-0.10	-1.80	0.57
ER	-0.04	220	1,021	0.06	4.64	-0.25	-1.14	0.07
Room and Board	-0.20	375	4,006	0.03	10.68	-0.36	-3.84	0.91
Non specialty visits	-0.25	293	948	0.10	3.23	-0.30	-0.98	0.38
Home visits	-0.01	12	3,156	0.69	274.11	-0.11	-29.90	0.34
Prevention	-0.02	50	125	0.21	2.48	-0.03	-0.08	0.02
Surgical procedures	0.07	87	616	0.01	7.12	-0.36	-2.57	-0.24
Surgical supplies/devices	-0.22	56	374	0.01	6.63	-0.32	-2.09	0.65
Specialty visits	-0.32	708	3,364	0.09	4.75	-0.35	-1.67	0.71
Dialysis	0.02	30	6,239	0.49	205.99	-0.19	-39.37	-0.87
PT, OT, speech therapy	-0.15	99	848	0.14	8.60	-0.18	-1.51	0.29
Chiropractic	-0.23	26	329	0.41	12.79	-0.05	-0.62	0.24
CAT scans	-0.15	63	518	0.07	8.28	-0.31	-2.53	0.44
Mammograms	-0.11	31	213	0.28	6.80	-0.10	-0.68	0.16
MRIs	-0.29	74	451	0.08	6.13	-0.30	-1.81	0.66
PET scans	-0.17	7	289	0.17	44.33	-0.16	-7.22	1.29
Radiology - diagnostic	-0.15	72	306	0.03	4.28	-0.39	-1.67	0.33
Ultrasounds	-0.14	32	137	0.04	4.23	-0.20	-0.85	0.20
Diagnostic services	-0.15	117	615	0.03	5.26	-0.38	-1.99	0.37
DME	-0.18	27	432	0.11	15.81	-0.23	-3.57	0.68
Ambulances	-0.07	24	181	0.01	7.57	-0.31	-2.36	0.19
ϕ = derivative of profit with respect to expected spending								1.64E-05
σ_π = standard deviation of individual profit								58,243
δ = spending mark-up								0.2

Table A-2 – Detailed results of selection incentive components by type of service with risk adjustment

	Age-sex risk adjustment			Prospective risk adjustment			Concurrent risk adjustment		
	$\rho_{\hat{m}_s,\pi}$	EM index	Full selection elasticity	$\rho_{\hat{m}_s,\pi}$	EM index	Full selection elasticity	$\rho_{\hat{m}_s,\pi}$	EM index	Full selection elasticity
All Spending	-0.47	-3.14	1.51	-0.25	-1.66	0.92	-0.28	-1.85	0.85
Outpatient	-0.42	-3.02	0.94	-0.22	-1.58	0.58	-0.25	-1.78	0.53
Inpatient	-0.37	-2.81	1.04	-0.15	-1.12	0.56	-0.16	-1.18	0.51
Pharmaceutical	-0.31	-3.75	1.69	-0.20	-2.39	1.14	-0.22	-2.66	1.03
Maternity	-0.03	-0.24	0.09	-0.01	-0.10	0.08	-0.01	-0.11	0.08
MH/SA	-0.10	-1.84	0.58	-0.06	-0.99	0.39	-0.06	-1.15	0.37
ER	-0.23	-1.08	0.07	-0.09	-0.42	0.05	-0.09	-0.43	0.04
Room and Board	-0.33	-3.52	0.84	-0.13	-1.38	0.43	-0.14	-1.44	0.38
Non specialty visits	-0.26	-0.85	0.35	-0.10	-0.31	0.25	-0.10	-0.32	0.24
Home visits	-0.11	-30.08	0.33	-0.08	-21.52	0.22	-0.08	-20.83	0.17
Prevention	-0.02	-0.04	0.02	-0.01	-0.01	0.02	0.00	-0.01	0.02
Surgical procedures	-0.31	-2.23	-0.21	-0.12	-0.86	-0.12	-0.13	-0.91	-0.11
Surgical supplies/devices	-0.26	-1.70	0.57	-0.09	-0.61	0.33	-0.09	-0.62	0.31
Specialty visits	-0.29	-1.40	0.63	-0.12	-0.56	0.40	-0.13	-0.59	0.38
Dialysis	-0.19	-39.36	-0.86	-0.12	-23.86	-0.49	-0.14	-29.62	-0.47
PT, OT, speech therapy	-0.15	-1.28	0.27	-0.05	-0.42	0.16	-0.05	-0.41	0.15
Chiropractic	-0.03	-0.43	0.21	-0.01	-0.15	0.17	-0.01	-0.19	0.17
CAT scans	-0.27	-2.26	0.41	-0.10	-0.83	0.22	-0.11	-0.88	0.20
Mammograms	-0.03	-0.17	0.11	-0.01	-0.05	0.10	-0.01	-0.05	0.10
MRIs	-0.26	-1.58	0.61	-0.10	-0.61	0.37	-0.11	-0.68	0.35
PET scans	-0.15	-6.82	1.22	-0.05	-2.31	0.49	-0.05	-2.42	0.43
Radiology - diagnostic	-0.32	-1.38	0.29	-0.12	-0.53	0.18	-0.13	-0.55	0.17
Ultrasounds	-0.15	-0.62	0.17	-0.05	-0.23	0.13	-0.06	-0.24	0.13
Diagnostic services	-0.33	-1.72	0.34	-0.13	-0.68	0.20	-0.13	-0.71	0.19
DME	-0.21	-3.30	0.63	-0.09	-1.43	0.34	-0.07	-1.15	0.27
Ambulances	-0.29	-2.20	0.18	-0.12	-0.88	0.10	-0.12	-0.90	0.09
ϕ = derivative of profit with respect to expected spending			1.64E-05			1.64E-05			1.64E-05
σ_π = standard deviation of individual profit			57,669			52,946			40,898
δ = spending mark-up			0.2			0.2			0.2

Table A-3 – Detailed results of selection incentive components by type of service with reinsurance

	Reinsurance			Reinsurance and concurrent Dx risk adjustment		
	$\rho_{\hat{m}_s,\pi}$	EM index	Full selection elasticity	$\rho_{\hat{m}_s,\pi}$	EM index	Full selection elasticity
All Spending	-0.53	-3.56	1.09	-0.29	-1.96	0.64
Outpatient	-0.43	-3.09	0.64	-0.20	-1.43	0.37
Inpatient	-0.43	-3.24	0.77	-0.16	-1.21	0.40
Pharmaceutical	-0.42	-5.07	1.37	-0.34	-4.05	0.91
Maternity	-0.04	-0.39	0.09	-0.03	-0.25	0.08
MH/SA	-0.13	-2.31	0.47	-0.11	-1.95	0.36
ER	-0.29	-1.33	0.06	-0.14	-0.66	0.04
Room and Board	-0.37	-3.95	0.60	-0.13	-1.37	0.29
Non specialty visits	-0.37	-1.18	0.32	-0.16	-0.51	0.23
Home visits	-0.08	-20.61	0.14	-0.03	-7.69	0.04
Prevention	-0.06	-0.16	0.02	-0.03	-0.07	0.02
Surgical procedures	-0.40	-2.83	-0.17	-0.14	-1.03	-0.09
Surgical supplies/devices	-0.38	-2.53	0.51	-0.14	-0.96	0.29
Specialty visits	-0.42	-1.99	0.56	-0.18	-0.84	0.35
Dialysis	-0.12	-25.34	-0.33	-0.05	-9.55	-0.10
PT, OT, speech therapy	-0.23	-1.99	0.25	-0.11	-0.93	0.16
Chiropractic	-0.08	-1.05	0.23	-0.05	-0.65	0.18
CAT scans	-0.34	-2.80	0.32	-0.13	-1.06	0.18
Mammograms	-0.16	-1.09	0.15	-0.03	-0.18	0.10
MRIs	-0.37	-2.24	0.53	-0.18	-1.12	0.34
PET scans	-0.16	-7.23	0.79	-0.05	-2.11	0.28
Radiology - diagnostic	-0.46	-1.97	0.26	-0.18	-0.76	0.16
Ultrasounds	-0.27	-1.15	0.18	-0.11	-0.46	0.13
Diagnostic services	-0.43	-2.27	0.28	-0.17	-0.91	0.17
DME	-0.25	-3.89	0.47	-0.09	-1.42	0.23
Ambulances	-0.32	-2.44	0.13	-0.12	-0.91	0.08
ϕ = derivative of profit with respect to expected spending			1.64E-05			1.64E-05
σ_π = standard deviation of individual profit			32,293			21,906
δ = spending mark-up			0.2			0.2

Table A-4 – Comparison of full selection elasticities across subgroups: year groups and family type – No risk adjustment

	Year groups			Single/family coverage	
	2008-2009	2010-2012	2013-2014	Single	Family
All Spending	1.35	1.60	1.91	1.55	1.61
Outpatient	0.86	0.98	1.19	1.01	0.99
Inpatient	1.03	1.11	1.25	1.03	1.14
Pharmaceutical	1.32	1.86	2.27	1.62	1.85
Maternity	0.09	0.09	0.09	0.08	0.10
MH/SA	0.50	0.53	0.71	0.53	0.59
ER	0.06	0.07	0.07	0.07	0.07
Room and Board	0.91	0.87	1.03	0.83	0.93
Non specialty visits	0.36	0.38	0.41	0.40	0.37
Home visits	0.22	0.34	0.42	0.17	0.38
Prevention	0.02	0.02	0.02	0.02	0.02
Surgical supplies/devices	0.59	0.65	0.73	0.58	0.67
Specialty visits	0.63	0.72	0.77	0.73	0.69
PT, OT, speech therapy	0.28	0.29	0.32	0.29	0.29
Chiropractic	0.26	0.23	0.20	0.22	0.24
CAT scans	0.37	0.45	0.55	0.44	0.44
Mammograms	0.16	0.16	0.16	0.15	0.16
MRIs	0.61	0.66	0.74	0.64	0.67
PET scans	1.07	1.29	1.56	1.16	1.33
Radiology - diagnostic	0.31	0.33	0.37	0.33	0.33
Ultrasounds	0.19	0.20	0.20	0.19	0.20
Diagnostic services	0.34	0.37	0.42	0.35	0.38
DME	0.66	0.68	0.68	0.53	0.72
Ambulances	0.17	0.18	0.23	0.19	0.19
σ_π = standard deviation of individual profit	49,071	59,061	67,861	64,259	56,565
δ = spending mark-up	0.2	0.2	0.2	0.2	0.2
Correlation with base case	0.989	0.999	0.997	0.994	0.9994

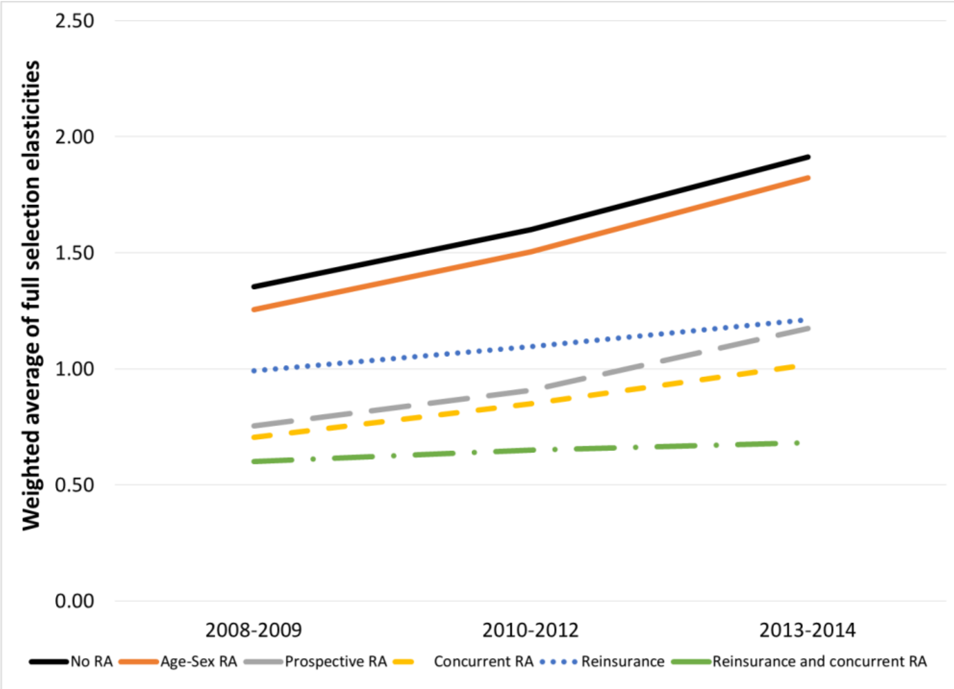
Table A-5 – Comparison of full selection elasticities across subgroups: age and RRS groups

	Age groups				Prospective RRS intervals			
	0 to 5	6 to 20	21 to 45	46 to 64	0 to .99	1 to 1.99	2 to 3.99	4 or more
All Spending	1.94	1.80	1.37	1.54	0.44	0.50	0.67	3.45
Outpatient	1.10	0.86	0.87	1.01	0.27	0.29	0.41	2.66
Inpatient	2.52	1.51	0.87	1.04	0.31	0.32	0.35	1.84
Pharmaceutical	1.45	2.98	1.60	1.54	0.58	0.68	0.93	2.99
Maternity	0.18	0.10	0.11	0.09	0.08	0.08	0.07	-0.06
MH/SA	1.06	0.57	0.59	0.54	0.28	0.36	0.48	0.76
ER	0.05	0.05	0.07	0.08	0.03	0.04	0.04	0.16
Room and Board	1.78	1.37	0.79	0.77	0.21	0.22	0.26	1.37
Non specialty visits	0.32	0.30	0.34	0.41	0.21	0.21	0.24	0.79
Home visits	0.64	0.67	0.30	0.15	0.02	0.05	0.07	0.40
Prevention	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
Surgical supplies/devices	1.78	0.60	0.55	0.58	0.25	0.24	0.27	0.63
Specialty visits	0.79	0.53	0.60	0.68	0.30	0.30	0.35	1.25
PT, OT, speech therapy	0.62	0.29	0.22	0.28	0.14	0.14	0.16	0.39
Chiropractic	0.21	0.20	0.22	0.21	0.18	0.17	0.17	0.04
CAT scans	0.52	0.27	0.35	0.46	0.14	0.14	0.17	0.77
Mammograms	0.07	0.11	0.14	0.12	0.12	0.10	0.10	0.07
MRIs	1.46	0.56	0.56	0.65	0.26	0.27	0.33	1.00
PET scans	1.74	1.49	1.30	1.19	0.19	0.20	0.29	1.51
Radiology - diagnostic	0.41	0.25	0.27	0.31	0.13	0.14	0.16	0.54
Ultrasounds	0.29	0.19	0.18	0.19	0.12	0.12	0.14	0.26
Diagnostic services	0.59	0.40	0.32	0.34	0.14	0.14	0.16	0.61
DME	2.72	1.29	0.52	0.53	0.17	0.18	0.21	0.95
Ambulances	0.59	0.12	0.15	0.19	0.06	0.06	0.08	0.43
σ_π = standard deviation of individual profit	49,113	42,255	48,476	74,922	28,737	48,234	72,362	219,751
δ = spending mark-up	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Correlation with base case	0.743	0.941	0.993	0.991	0.876	0.878	0.892	0.939

Table A-6 – Sensitivity analysis for ϕ (derivative of plan choice probability with respect to expected spending) for no risk adjustment and prospective risk adjustment cases, using full sample

	No risk adjustment			Concurrent risk adjustment		
	Full selection elasticity for			Full selection elasticity for		
	0.5ϕ	ϕ	2ϕ	0.5ϕ	ϕ	2ϕ
All Spending	0.99	1.60	2.82	0.61	0.85	1.31
Outpatient	0.62	0.99	1.75	0.39	0.53	0.82
Inpatient	0.70	1.11	1.95	0.39	0.51	0.73
Pharmaceutical	1.08	1.80	3.22	0.70	1.03	1.69
Maternity	0.09	0.09	0.11	0.08	0.08	0.09
MH/SA	0.39	0.57	0.94	0.29	0.37	0.53
ER	0.05	0.07	0.10	0.04	0.04	0.05
Room and Board	0.55	0.91	1.62	0.29	0.38	0.57
Non specialty visits	0.29	0.38	0.56	0.22	0.24	0.28
Home visits	0.17	0.34	0.66	0.09	0.17	0.33
Prevention	0.02	0.02	0.02	0.02	0.02	0.02
Surgical supplies/devices	0.43	0.65	1.08	0.26	0.31	0.39
Specialty visits	0.49	0.71	1.14	0.33	0.38	0.48
PT, OT, speech therapy	0.21	0.29	0.46	0.14	0.15	0.18
Chiropractic	0.19	0.24	0.32	0.16	0.17	0.18
CAT scans	0.29	0.44	0.75	0.17	0.20	0.28
Mammograms	0.13	0.16	0.22	0.10	0.10	0.10
MRIs	0.45	0.66	1.08	0.30	0.35	0.46
PET scans	0.73	1.29	2.41	0.30	0.43	0.69
Radiology - diagnostic	0.23	0.33	0.53	0.15	0.17	0.22
Ultrasounds	0.15	0.20	0.28	0.12	0.13	0.14
Diagnostic services	0.25	0.37	0.62	0.16	0.19	0.25
DME	0.41	0.68	1.20	0.21	0.27	0.39
Ambulances	0.13	0.19	0.32	0.08	0.09	0.13
ϕ = derivative of profit with respect to expected spending	8.199E-06	1.64E-05	3.280E-05	8.199E-06	1.64E-05	3.280E-05
σ_π = standard deviation of individual profit	58,243	58,243	58,243	40,898	40,898	40,898
δ = spending mark-up	0.2	0.2	0.2	0.2	0.2	0.2
Correlation with base case	0.996	1.000	0.998	0.953	0.964	0.962

Figure A-1 – Evolution of the full selection elasticities for all spending over time (deflated)



APPENDIX B

Heterogeneity in demand response

The main text focuses on the case in which all consumers have the same demand elasticity for a given service. In this appendix we extend our main analysis by allowing different groups of individuals (such as young vs old, male vs female, healthy vs sick) to have different demand elasticities, while keeping them constant within groups. This framework generalizes to any number of consumer groups and, in the limit, to the case in which each group corresponds to an individual. The number of groups can be defined by the amount of individuals such that their elasticities are roughly the same, provided that these can be estimated.

Using $\partial \pi\,(q)/\partial\, q_s$, as defined previously in equation (3), and letting $q_s = 1$ we obtain:

$$\frac{\partial \pi(q)}{\partial q_s} = (1 - c_s) \sum_i \{\phi \left(\frac{q_s \widehat{m}'_{is}}{\widehat{m}_{is}}\right) \widehat{m}_{is} \pi_i - n_i \left(\frac{q_s m'_{is}}{m_{is}}\right) m_{is}\}$$

We can now partition the summation into J mutually exclusive groups (denoted with superscripts), each of which has its own demand elasticity that is fixed within each group, i.e., $\eta_{is} = \eta_s^j \; \forall \; i \,\epsilon\, j = 1,2, \dots, J$.

$$\frac{\partial \pi(q)}{\partial q_s} = \sum_{j=1}^{J} (1 - c_s) \sum_{i\,\epsilon\, j} \left\{\phi \left(\frac{q_s \widehat{m}'_{is}}{\widehat{m}_{is}}\right) \widehat{m}_{is} \pi_i - n_i \left(\frac{q_s m'_{is}}{m_{is}}\right) m_{is}\right\}$$

$$= \sum_{j=1}^{J} (1 - c_s) \eta_s^j \sum_{i\,\epsilon\, j} \{\phi \widehat{m}_{is} \pi_i - n_i m_{is}\} \times \frac{N^j \overline{m}_s^j}{N^j \overline{m}_s^j}$$

$$= \sum_{j=1}^{J} (1 - c_s) \eta_s^j \left(\phi \sum_{i\,\epsilon\, j} \frac{\widehat{m}_{is} \pi_i}{N^j \overline{m}_s^j} - 1\right) \times N^j \overline{m}_s^j$$

$$= \sum_{j=1}^{J} (1 - c_s) \eta_s^j \left(\sigma_\pi^j \phi \frac{\sigma_{\widehat{m}_s}^j}{\overline{m}_s^j} \rho_{\widehat{m}_s, \pi}^j - 1\right) \times N^j \overline{m}_s^j$$

The full selection elasticity becomes, then:

$$FSE = \frac{\partial \pi(q)}{\partial q_s} \times \frac{1}{N\bar{m}_s} = \sum_{j=1}^{J} (1 - c_s)\eta_s^j \left(\sigma_\pi^j \phi \frac{\sigma_{\widehat{m}_s}^j}{\bar{m}_s^j} \rho_{\widehat{m}_s,\pi}^j - 1 \right) \times \frac{N^j \bar{m}_s^j}{N\bar{m}_s} =$$

$$= \sum_{j=1}^{J} FSE^j \times \frac{N^j \bar{m}_s^j}{N\bar{m}_s} \tag{B1}$$

The final solution shows that the full selection elasticity that we estimate is a weighted average of the group-specific selection index, in which the weights correspond to the fraction of total spending by each group. To the extent that heterogeneity between consumers exists, equation (B1) shows that it is only relevant insofar those consumers have enough medical consumption as a fraction of the total. Equation (B1) is attractive since it shows that selection indices can be calculated for each individual group separately and then aggregated for all consumers, given appropriate estimates of group-specific demand elasticities.

The consumer heterogeneity problem that we face is akin to the firm price-discrimination problem, in which a firm would like to set a different price for different consumers but is unable to do so and bases itself on aggregate demand instead. The price elasticity for the aggregate demand is of the same form of equation (B1), given by the individual group elasticities and weighted by the fraction of each group consumption on the overall quantity.

From a plan design point of view, plans would like to enroll only healthy individuals, but are unable to do so due to their contracts with employers. For that reason, we focus on the narrowest group that can be used for selection, which is the services provided, instead of groups formed by individuals' characteristics.