Demand Elasticities and Service Selection Incentives among Competing Private Health Plans

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Abstract: We examine both selection incentives and the extent of actual service-level selection by health plans while broadening the Ellis and McGuire (2007) selection index to reflect not only variation in service predictability and predictiveness but also variation in cost sharing, risk-adjusted profits, and demand elasticities across 33 disaggregated types of service. Using privately-insured claims data from 73 large employers from 2007-2014, our improved selection elasticity shows that comprehensive and preferred provider organization health plans have the strongest selection incentives. Compared to flat capitation, concurrent risk adjustment reduces the elasticity by 45%, prospective risk adjustment by 40%, simple reinsurance system by 25%, and combined concurrent risk adjustment with reinsurance by 54%. Reinsurance significantly reduces the variability of individual-level profits, but increases the correlation of expected spending with profits, which strengthens selection incentives. Finally, consumer-driven and high deductible health plans and HMOs show stronger evidence of actual selection than other plan types.

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 much more difficult to regulate service-level selection, the supply-side availability of specific types of providers or types of services. Service-level selection is particularly easy when health plans can design benefit plan 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 four contributions. First, we expand the analytical framework to include variation in benefit plan cost sharing paid by consumers, which can influence selection and plan profits. Second, we improve the empirical measure of service-level selection incentives by incorporating not only this cost sharing for each service, but also including new information about 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. Finally, we examine not only the incentive to select but also the magnitude of actual selection across seven health plan types, notably including three newly-popular plan types that restrict access to certain services using either supply- or demand-side incentives.

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) show that selection incentives can be measured as 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) (henceforth EJK) was the first paper to actually examine whether plans behave as predicted by the EM selection model.[1] They also examine whether prospective, diagnosis-based risk adjustment reduces these service distortion incentives.[2] One 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. Our study is the first study to incorporate empirical estimates of four other terms that affect the calculation of service-level selection incentives: (1) demand-side cost sharing, (2) service-level demand elasticities, (3) individual-level profit variation, and (4) demand responsiveness

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[1] Other empirical studies have demonstrated that managed care plans and non-managed care plans provide different levels of spending on various services, including Cao and McGuire (2003) and Eggleston and Bir (2007), but these studies do not test whether the services over- or under-supplied by managed care plans are the services identified by the theoretical literature as most profitable to do so.

[2] In a recent paper, Layton et al. (2017) (LEMvK) provide an excellent 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. Their approach differs in that they formally model consumer and plan level premiums which we do not. The framework used in their metric for service selection is similar to the EM index, except that LEMvK characterizes optimal service levels in quantity terms rather than shadow prices. Hence, while LEMvK characterize incentives using the derivative of profits and benefits with respect to quantity choices, we follow EM and characterize it in terms of shadow price choices.

of health insurance enrollment to expected spending. Doing so requires that we enrich the EM formulation to incorporate service and plan level variation in cost sharing. We show below how these four 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 that could be readily incorporated in their calculation. Here, we take advantage of the results from Ellis, Martins and Zhu (2016) (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, leveraging differences between plans such as preferred provider organizations (PPOs) and health maintenance organizations (HMOs) where cost sharing is essentially 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 for the employer 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.

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: high cost sharing services become somewhat 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 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. Our most surprising result is that 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 correlation between service-level spending and reinsured total spending, hence improving the predictiveness of some services.

As in EJK, we examine not only incentives to select, but also the extent to which various health plan types show evidence of actual selection. We find that HDHPs and CDHPs are similar to HMOs and show signs of significant selection distortions in the services they actually provide (although their mechanisms are different, with the first two influencing selection by demand rather than supply side plan features). We also find in these plan types that services predicted to have the highest incentive to underprovide appear to be underprovided. By contrast, EPOs and PPOs show an opposite relationship between selection incentives and actual spending on specific services relative to expected levels: services appear to be overprovided where the incentive to underprovide is greatest.

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. We note that our new sample of employer-based health plans provides a valid environment for examining selection incentives and actual selection distortions. Section II reviews the Ellis-McGuire Selection Index which we extend and call the full selection elasticity (FSE) since we estimate a proper elasticity, not a component of the selection elasticity as in EM. 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 suggestion for future research.

I. Background

Recent theoretical and empirical studies in the health care literature, summarized carefully 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. These plans have more leverage over the type of service supplied both because they are more closely involved in selecting providers with whom to contract and also because they are able to specify the constraints under which providers work. 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 in the US, 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 that are covered. 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. Exclusive provider organizations (EPOs) restrict provider choice to relatively narrow panels of doctors and hospitals, making it relatively easy to favor or discourage selected services identified as being profitable or unprofitable given selection incentives. In contrast, consumer-driven health plans (CDHP), and high deductible health plans (HDHP) charge both higher deductibles and higher coinsurance rates, which also may allow favoring or discouraging services selectively through their benefit coverage. A key research question that has not yet been answered is whether narrow provider panels (HMOs and EPOs) or stingy benefit designs (CDHP and HDHP) 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 "risk adjustment" to change incentives. The most common form of risk adjustment used is diagnosis-based risk adjustment, 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. Two alternate forms of risk adjustment are typically used. Prospective models use only information prior to the start of the prediction period, while concurrent models (also sometimes called retrospective 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, a second strategy for reducing such incentives is reinsurance, 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 and the magnitude of actual selection distortions 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. Finally, premium differences may be allowed to vary with expected costs more with employment-based plans than in public programs where premiums are based on pre-specified risk adjustment or premium age-gradient formulas. While we agree that incentives will vary, we think it is still informative to examine incentives and their consequences in our sample. First, EJK, which uses data from the same market as we do, find that incentives to select are very similar across plan types: the incentives are there, what varies is only how much plans and consumers act upon them. Second, we find that more than 85 percent of the employer years in our estimation sample offer multiple health plans, with the median employer offering three health plans, creating potential benefits to service selection. Third, even if an employer is offering only one plan, there is still the important margin in which employees choose where to work, and married employees with dual employed household members may get to choose which employer's health plan to insure each family member under. Not all employees need to have such choices in order for selection incentives to remain relevant to health plans. Finally, even a health plan offering multiple health plan types may negotiate different profit incentives for different plans. For example, the insurer's PPO plan may be an administrative-services-only plan (with very weak selection incentives), while its HMO plan may be at-risk, with strong selection incentives. We present evidence below that responsiveness to selection incentives varies at the plan type level in ways that are consistent with these incentives.

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

Our estimation builds on the Ellis-McGuire (2007) selection index (which also is used by EJK), which we re-derive here with three refinements. First, we allow for variation in service-level elasticities of demand, η_s, which are assumed constant in the original EM and EJK formulations. Second, we examine payment systems in which the standard deviation of individual level profitability, σ_π, can be changed with risk adjustment or reinsurance. 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 expand the EM selection index to accommodate differences in demand-side cost sharing between services at the plan type level.

The EM model starts with the assumption 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 favorable (profitable) individuals and avoid unprofitable ones.

Individuals choose their health plan based on their expected covered spending on each service s, $\hat{m}_s$. 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_{is} and m_i be the corresponding amounts that the plan *actually* spends on individual i.

We assume that the utility of individual i from a plan[3] can be written as

$$u_i(\hat{m}_i) = v_i(\hat{m}_i) - c \times \hat{m}_i + \mu_i \qquad (1)$$

The utility from consuming each service is additively separable in expected spending on each service, $v_i(\hat{m}_i) = \sum_s v_{is}(\hat{m}_{is})$, which implies that all cross price effects are zero. The second term, an extension over the previous literature, captures the idea that the individual gets disutility from out-of-pocket payments, which are the sum across all services of the average cost share, c_s, for that service and for that plan type times the expected spending for each service, $\hat{m}_{is}$.[4] The final term μ_i is a random term with distribution function Φ_i, discussed further below. The individual i chooses this plan if $u_i(\hat{m}_i) > \bar{\mu}_i$, i.e., $\mu_i > \bar{\mu}_i - v_i(\hat{m}_i) + c \times \hat{m}_i$, where $\bar{\mu}_i$ is the valuation the individual places on the next best alternative plan.

We assume that the competitive health plan uses shadow prices to efficiently ration the amount of each health care service that each patient receives. Let q_s denote the shadow price a plan sets for service s. Following Glazer and McGuire (2000) and EM, we use the

[3] We avoid giving plan index suffixes to simplify model notation, but the implications are clear.
[4] We could build a separate model of expected out-of-pocket spending, but for simplicity we use instead the plan average cost share multiplied by the individual's expected spending on that service, $\hat{m}_{is}$. We discuss how we implement this empirically below.

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 $v'_{is}(\widehat{m}_{is}) = q_s$.[5]

The plan chooses its vector of shadow prices $q = \{q_1, q_2, \cdots, q_S\}$ to maximize its profits

$$\pi(q) = \sum_i n_i(\widehat{m}_i(q))\pi_i \,, \tag{2}$$

where $n_i(\widehat{m}_i) = 1 - \Phi(\bar{\mu}_i - v_i(\widehat{m}_i) + c \times \widehat{m}_i)$ is the probability that health plan expects individual i would choose the plan; $\pi_i = r_i - \sum_s(1 - c_s)m_{is}\,(q_s)$ is the actual profit the plan receives for each individual where r_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 total plan cost of covering individual i for using services covered by the plan.

The derivative of profit with respect to q_s is

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

$$= \sum_i \frac{\partial}{\partial q_s}\{[1 - \Phi_i(\bar{\mu}_i - v_i(\widehat{m}_i) + c \times \widehat{m}_i)][r_i - \sum_s(1 - c_s)m_{is}\,(q_s)]\}$$

Applying the assumption of no cross-price effect, we have,

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

$$= \sum_i\{\Phi'_i(v'_{is}\widehat{m}'_{is} - c_s\widehat{m}'_{is})\pi_i - n_i(1 - c_s)m'_{is}\}$$

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 $\Phi'_i = \phi$.[6] Then we have,

[5] The explicit method of rationing used for different services is not specified in Glazer and McGuire or EM, but deserves mention. We do not assume waiting time or inconvenience ("hassle factors") are 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 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.

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

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

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

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

The above expression includes terms that are elasticities of demand of actual spending and expected spending. Since we know no literature that informs us of how the two differ, we assume that they are the same, so that $\frac{q_s \widehat{m}_{is}^{'}}{\widehat{m}_{is}} = \frac{q_s m_{is}^{'}}{m_{is}} \equiv \eta_{is}$,[7] then the above can be rewritten as,

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

We assume that all individuals share the same elasticity of demand for each service but elasticities can differ across services, i.e., $\eta_{is} = \eta_s$.[8] Then we have,

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

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) also calculate our welfare metric at the value $q_s = 1$.[9] Taken together, we have,

[6] 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.

[7] We allow individual expected spending to be different from the actual. However, here we assume that their expectation is the same and that they have the same derivative with respect to the shadow price. Actual individual spending can still have more noise despite these assumptions.

[8] 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.

[9] 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.

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

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

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:

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

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

Hence the full selection elasticity is at its core a cross product of expected spending on service s, $\hat{m}_{is}$, and the individual's profitability to the plan.

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 and plan level profits at the individual level. We can then rewrite the full selection elasticity as:

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

Under our assumption of perfectly competitive health plans, competition drives profits down to zero so that $\overline{\pi} = 0$, and the full selection elasticity can be written as:

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

Note that expression (5) is a unit free measure consistent with the original definition of FSE_s as an elasticity. The formula contains six 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 four 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 profits, and (4) ϕ, the density of distribution of individual specific valuation of health insurance. These four terms were assumed to be constant across plan types and services in EM and EJK, so that they change only the magnitude but not the order of rank in the selection index.[10] In this paper we relax this assumption and show that three of these terms not only affect both the magnitude and the ranking of selection incentives but they also matter empirically by magnifying or mitigating how "predictability" and "predictiveness" shape selection incentives. For this reason, our FSE has an economic meaning, it gives the change in profits given an unit increase in the shadow price, as a fraction of total spending, and can be interpreted on its own. This is in contrast with the EM selection index that, since it only estimates two terms, is only relevant in a relative sense, i.e., as an ordinal term.

The term $(1 - c_s)$, 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.[11]

The demand elasticity can vary across services. As an example of how price elasticities of demand can vary across services, 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 ($\eta_s = -0.05$).

More recently Brot-Goldberg et al (2017) estimate price elasticities of demand by taking advantage of a large exogenous change in cost sharing before and after a large

[10] 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.

[11] 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.

employer (covering approximately 100,000 lives) switched from offering two plans to offering only one plan with a high deductible. Overall they find that total spending declined by 11 to 15 percent depending on their model of consumer expectations. They find that consumers respond heavily to changes in the spot prices, suggesting strongly myopic expectations by consumers of cost sharing before and after exceeding high deductibles. Of particular relevance to our study is that they also examine responsiveness of spending for ten categories of spending that parallel our type of service categories, as well as for 30 high volume procedures. They find the largest treatment effect (of the plan benefit design change) for ER use, brand name pharmacy spending, and "other", and the lowest change for inpatient hospital spending, mental health and prevention. Although it might be informative to synthesize their and other estimates of demand response into our calculations, for this paper, we rely solely on the elasticities provided in EMZ, which has the advantage that they are based on the same very large sample and use congruent type of service spending categories.

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 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. [12]

The above expression for the full selection elasticity can also be motivated heuristically in the following way. We are interested in characterizing services for which decreased spending is associated with increased profits. We therefore expect these services to have the property that the covariance of profits with spending on these services is negative (providing less of this service increases profits). But consumers do not base their enrollments on realized spending but rather on expected spending. Hence consumers use expected rather

[12] 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.

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.

In terms of empirical implementation, both the predictability and predictiveness terms can be empirically estimated, as in EM and EJK. This paper adds in three more empirical components of the index. The standard deviation of profits across individuals, σ_{π}, and the insurer's cost share, $(1 - c_s)$, can be readily calculated from the data.[13] The demand elasticities for service s, η_s, use new results from EMZ. The one term in the formula that is difficult to estimate an empirical counterpart to is ϕ, the density of distribution of individual specific valuation for health insurance. It regards the change in the probability of person joining a health plan from a change in expected spending by one dollar on medical care, ${\partial n_i}/{\partial M_i}$ or even more ambitiously ${\partial n_i}/{\partial m_{is}}$, how a change in expected spending on a specific health care service in a health plan affects the probability of choosing that health plan. In Section IV, we discuss how we estimate this term empirically.

In order to understand the consequences of risk adjustment, in the analysis below 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

[13] Following FGM, EM, EJK, and Layton et al (2017) we focus on zero profit plan payment systems, such that total payments equal total covered costs. Actual plan payment will typically include a profit margin, which reduces the incentive to underprovide all services. Actual plan payment systems may also reflect special contracts between the health plan and the employers, which we do not observe, such as cost targets or performance bonuses. Our approach is typical of a broad set of studies that worry about relative rather than absolute profit incentives.

reinsurance program in the absence of any risk adjustment and a combination of reinsurance and concurrent risk adjustment. The reinsurance system we examine mimics the system in place from 2014-2017 in the ACA Health Insurance Marketplace, and the combination of concurrent risk adjustment and reinsurance approximates the impact of both programs that were in place over that period.

III. Data

We use the Truven Analytic's MarketScan commercial claims and encounters data from 2007 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 and family coverage) with at least two consecutive years of eligibility and claims information that include both pharmacy and mental health/substance abuse coverage. We require that no individual changed plans during a calendar year, although we allow switches on January 1 of each year. The first year of each person's claims and eligibility information are used to calculate lagged spending in each of 33 types of services.

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 33 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. An important unresolved issue is what information consumers use to select health plans. EM and EJK explored a variety of different information sets, which included age and gender only, prior year diagnostic information, and prior year spending information, based on aggregated and disaggregated categories of spending. For this paper we use the information found by these two previous studies 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 33 types of services from year t-1 to predict their likely spending on each of those same services in year t each year. 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 33 type of service categories, described further below. 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.

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, we need to separately calculate predictability and predictiveness, which requires predicting service level spending for the prediction year t using information from the prior year, t-1. We also need elasticities by type of service, and the standard deviation of individual level profits, which we can easily calculate from our data. Finally, we need an estimate of ϕ which we discuss below.

For service-level demand elasticities, we rely on new elasticity estimates from EMZ that rely on a new instrumental variables approach that exploits 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 plan-year, month, and individual fixed effects to calculate the differential demand response of individuals facing high or low cost shares doing a given calendar year. In effect, their estimator is using differences in consumption early in the year and at the end of the year for some individuals where costs shares decline sharply, while the cost share of other individuals remain constant. The authors overcome the endogeneity between spending and cost share using a novel instrumental variable technique, which is only 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 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 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.[14]

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 -0.6 for HDHP versus -0.3 for both HMOs and 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

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

to 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.

To obtain predicted service level spending, we use linear predictive model specifications. Some readers may be concerned that ordinary least squares model (OLS) may not appropriately capture classical features of health expenditures such a large proportion of zero expenditures and a long right trail. Although various advanced econometric methods, including generalized linear model specifications and two-part models using linear and transformed expenditures have been developed to accommodate these data features, 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.

We then turn to the information sets used for predictions. Both EM and EJK 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 dummies (based on Ash et al, 2000), and prior year service-level spending decomposed by type of service. Following 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.

$$\widehat{m}_{s,t} = f(age, gender, m_{1,t-1}, ..., m_{33,t-1}) .$$

One empirical challenge 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. So 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, weakly informed by our reading from the literature, that consumers are only half as responsive to expected spending changes as premiums, suggesting that the elasticity of plan choice to expected spending, $\widehat{M}_i$ is plausibly 0.3. To convert this into a slope rather than an elasticity, we multiply by the mean plan market share of the plans among all employer's 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, which is to say 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. After using this value, we conduct sensitivity analysis using 0.5ϕ and 2ϕ which bounds likely values, or at least is informative about the sensitivity of the ranking to this unknown parameter.

Our approach also benefits from its ability to quantify not only the incentive to select, but also the empirical reality of its extent: Do plans with capitated revenues engage in distortions of the type predicted by the selection incentives, and if so, how much? To do this, we follow the methodology of EJK and both test the associations statistically and examine patterns graphically. Specifically, for each plan type and each service, we calculate the percent of total plan spending on a given service in that plan type divided by the percent of spending on that same service for all plans. Hence if HMOs spend 15 percent of their health spending on service XYZ, while the average for all plan types on this type of service is 10 percent, then the ratio would be 15/10 = 1.5. A PPO plan spending 5 percent of its total on

XYZ would have a mean ratio of 5/10=.5. This normalization corrects for two concerns. The first concern is that some very expensive services have extremely low frequency, so their mean is small. This normalization finds the relative importance of the spending, not the absolute importance. The second concern this normalization addresses is to remove systematic price differences over time and across plan type. For example, if PPOs negotiate ten percent discounts across all services relative to Comprehensive plans, this will be reflected in their premiums, but this does not affect this ratio calculation. For a sensitivity analysis, we also include predictive ratios – the ratio of actual to predicted spending for each plan type – to see if plans show evidence of selection using this alternative metric. Predictive ratios correct for the first concern, but not the second.

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. Although our data span seven plan types, we focus on five that are of particular interest: EPO, HMO, PPO, CDHP and HDHP. The final column shows mean consumer cost shares by plan type, revealing that EPOs, HMOs and comprehensive plans have notably lower average cost shares than CDHP and HDHP, as expected.

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

Table 2 summarizes the basic components of the full selection elasticities for 33 type-of-service categories for our full sample under the assumption that there is no risk adjustment.[15] 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 58,196 with no risk

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

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 ($\rho_{\widehat{m}_s,\pi}$), 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 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 1.20 percent, with considerable variation across services.

Table 2 results show several interesting patterns. First, consider the EM index, which does not depend on any estimates of demand elasticity or other constants. It finds that the services most vulnerable to underprovision are home visits[16], dialysis, hospice care, and inpatient specialty drugs (which includes chemotherapy and other IV drugs). Unfortunately, the demand elasticities of dialysis and hospice services are imprecisely estimated and of the wrong sign. Also with elasticities of the wrong sign are “major surgical procedures” and “radiology – therapeutic.” 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

[16] 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.

column) are implausible, and we therefore omit these four services from the rest of our main analysis.[17]

The pattern in Table 2 has strong face validity, and is broadly consistent with the results in EJK using an earlier sample period on the same type of data. Of particular note is that both the EM and the new FSE metric identify pharmacy spending (FSE=1.33) as very prone to use for selection, with nonsurgical supplies/devices (FSE=1.09) and PET scans (FSE=0.94) also having high incentives for selection.[18] On the other extreme, prevention (FSE=0.01) and maternity (FSE=0.07) have extremely low elasticities. Demand elasticities are sufficiently low for home visits and transportation (i.e., ambulance expenses) that even though they have sizable incentives to select using the EM selection index, in our new FSE metric, they have low selection elasticities.

Table 3 recalculates our full selection elasticity for six payment systems on overall spending and the 29 (out of 33) services with statistically significant and plausible demand elasticities. The first column replicates the final column of Table 2, which corresponds to no risk adjustment. New to this table are the bottom three rows. The first row of these three is the mean spending-weighted selection index that is the weighted average of the 29 selection elasticities from that payment system. The next row has our estimate of the insurance demand response from offering one more dollar of spending. The final row shows σ_π, the standard deviation of individual level profits. In our base case, the standard deviation of individual profits is 58,196. 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

[17] Results for these services are presented in the Appendix A.
[18] As in Brot-Goldberg et al (2017) the category "other" has an above average elasticity, and hence a larger FSE of 1.04.

age-sex group. We see here that age sex adjustment has only a modest effect on incentives, lowering the average elasticity only from 0.56 to 0.53.

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 39 percent reduction (1 - 0.34/0.56) in average incentives to select, while concurrent risk adjustment achieves a 45 percent reduction in the weighted average.

The fifth column in Table 3 examine 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 \$32,291 which is an impressive 45 percent reduction from the no risk adjustment levels. But the average selection elasticity is 0.42, which is only a 25 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-2 and 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.[19]

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 0.56 in the base case to 0.26, a 54 percent reduction from the base case and a 9 percentage point 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, the weaker performance of simple reinsurance. This graphical 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

[19] 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.

variation. The demand elasticity was held constant for each calculation, since such elasticities were not computed at the service level for all such 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, is 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 HDHP 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 .94.

The first set of bars in Figure 2 summarize the weighted average FSE for our seven different plan types shown at the bottom of Table 4. Sample sizes are adequate for each simulation: Table 1 shows that even our least common plan type (EPO) still has information on 94,385 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 average full selection elasticities are modestly lower both for plan types that rely on supply side incentives such as EPOs, HMOs and POS, and for plan types such as HDHPs and CDHP that rely on demand side incentives. HDHP have an average full selection elasticity (0.49) that is comparable to HMOs (0.45), despite their very different selection approaches.

The next three segments of Figure 2 (derived from Appendix Table A-4) examine whether selection incentives vary over time, between single and family contracts, and by age group. 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.[20] The calculations by age group find stronger profit incentives to select against the old than against the younger adults, but surprisingly strong incentives to select against children aged 6 to 20. Note that 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 remain very small and will be attractive to provide generously across all age groups. The selection elasticities for the youngest age group are only correlated with overall selection at ρ=0.688, 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

[20] 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.

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 also 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, there is no noticeable difference in growth rates in all five measures.[21]

D. *Selection Incentives versus Actual Service Spending by Selected Groups*

So far we have confirmed that selection incentives are robust to alternative econometric specifications and consistent across plan types. We next turn to whether services predicted to have the strongest selection incentive are in fact supplied least generously by plans that typically receive fixed premiums. We do this for dimensions of primary interest, by plan type.

Figures 3 and 4 present our results graphically, first assuming no risk adjustment and then using concurrent risk adjustment. The horizontal axis in each diagram is our full selection elasticity calculated using the each plan type subsample, as in Table 4. The vertical axis measures the ratio of spending share for each service to the overall sample average spending share for each of four popular plan types. By construction, the weighted average across the full sample is one for each service. We have omitted the Comprehensive and POS plan types from the two figures to simplify the figure. Figure 3 shows that there are striking differences in how services are provided across plan types. For services with low selection elasticities, all five plan types provide very similar levels of services on average. For services with high full selection elasticities, we find a divergence. HDHPs and CDHPs are similar to

[21] 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.

HMOs in showing evidence of much lower rates of offering services that are attractive to undersupply, while PPOs and EPOs show evidence of offering relatively more of these services. We would have expected EPOs to be more like HMOs, but it is plausible that some of the EPOs are organized around distinguished medical centers (such as the ones at Boston University) and it is the intent of the EPO to attract members to that provider and its set of services that runs against a pure profit maximizing incentive for the plan. Figure 4 replicates that analysis for the payment system with concurrent risk adjustment. The selection elasticities are lower, but the same pattern emerges, suggesting that concurrent risk adjustment does not entirely remove the incentives for selection.[22]

The results in Figures 3 and 4 might be contaminated by adverse selection due to biased consumer plan type choice. For example, one plan type might spend a higher share in service X simply because its population is older or sicker for historic reasons, regardless of how generous the plan is. To correct for this, Figure 5 repeats the analysis of Figure 4 while using risk-adjusted predictions for each plan type and service level. For Figure 5, we again plot the full service elasticity on the horizontal axis, but plot predictive ratios for sending on each service on the vertical axis. That is, for each service and each plan type we calculate the ratio of actual spending on that service to predicted spending using a concurrent risk adjustment formula, and normalize this predictive ratio by the plan's average predictive ratio across all types of services. This measure can be interpreted as the relative difference between a plan actual spending and predicted one, while controlling for the overall average rate of over or underprovision. If it is above 1, then the plan spends more on that type of service than is predicted by concurrent risk adjustment. Values less than one imply underprovision. We view such differences as additional evidence from supply-side rationing.

[22] Figures 2 and 3 give the same result if we use the full sample to generate the FSE instead of the plan level estimates.

The lines in Figure 5 providing an analogous picture to Figure 4, showing similar correlations. For the sake of exposition, we truncate the predictive spending ratio at 2 for three services for which we had trouble estimating service elasticities (Home visits, Room and board – Surgical and Room and board – Medical). EPOs and PPOs show the same upward sloping pattern while HMOs, CDHPs and HDHPs show evidence of undersupplying services with higher full selection elasticities. Note, however, that for the HMOs, the correlation between the two variables seems to be driven by outliers, so that after removing these, HMOs show a flat trend below 1, showing evidence of equal underprovision across services.

E. *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 5. It is no surprise that the elasticities vary with ϕ, changing nearly proportionately when ϕ is doubled or halved. The full selection elasticities remain highly correlated as this key parameter is changed, with correlations in the no risk adjustment results correlated at 0.98, and those with concurrent risk adjustment correlated at 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 EM (2007), and refined by EJK (2013) to a large rich dataset, Thomson-Reuters MarketScan commercially insured data, for the period 2007-2014. We confirm the usefulness of the EM finding that selection incentives are strong for certain services commonly thought to be provided more by non-managed care than managed care commercial plans. But we also find new refinements that are missed in that earlier work. Demand elasticities, which capture how responsive spending on each service is to the degree of rationing or benefit coverage, vary meaningfully across different services, and enter into calculations of incentives to select. 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.

One result that surprised us is that we find evidence that 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. This makes under or oversupplying specific services 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 the lower selection incentive of 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.

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 45%, and a combination of risk adjustment and reinsurance reduces the incentive by 54%. 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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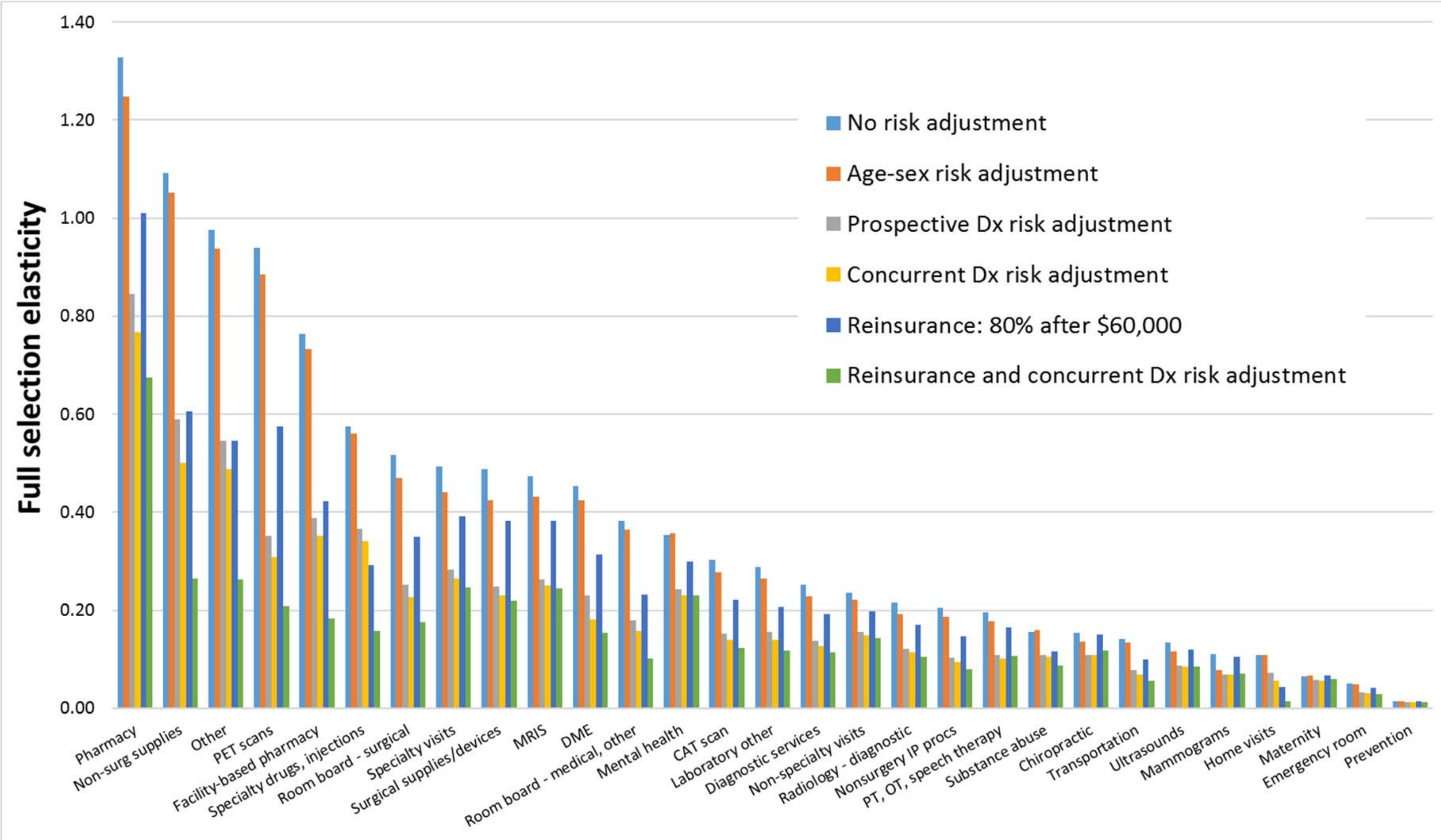
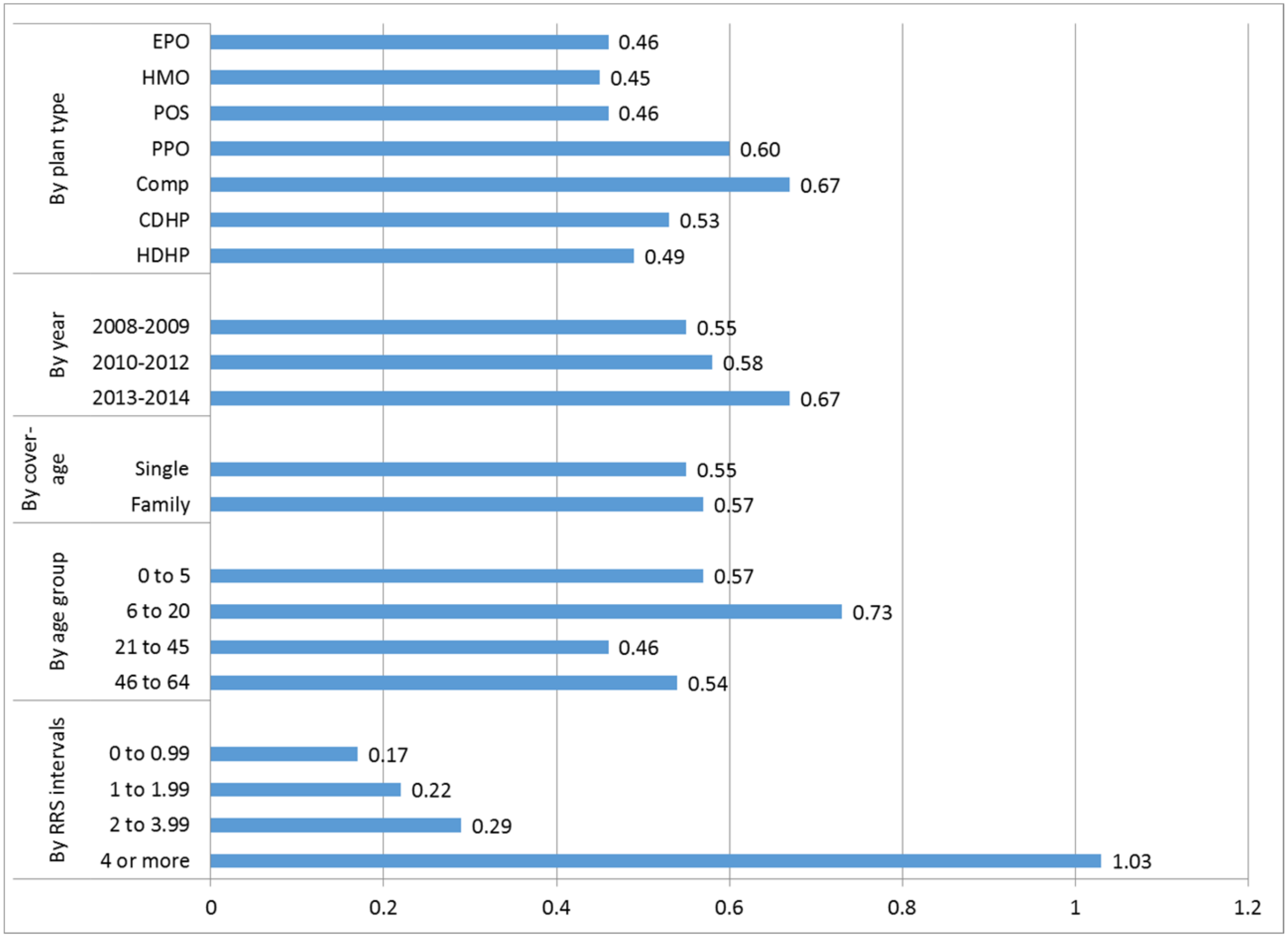
Figure 1 – Full selection elasticity results



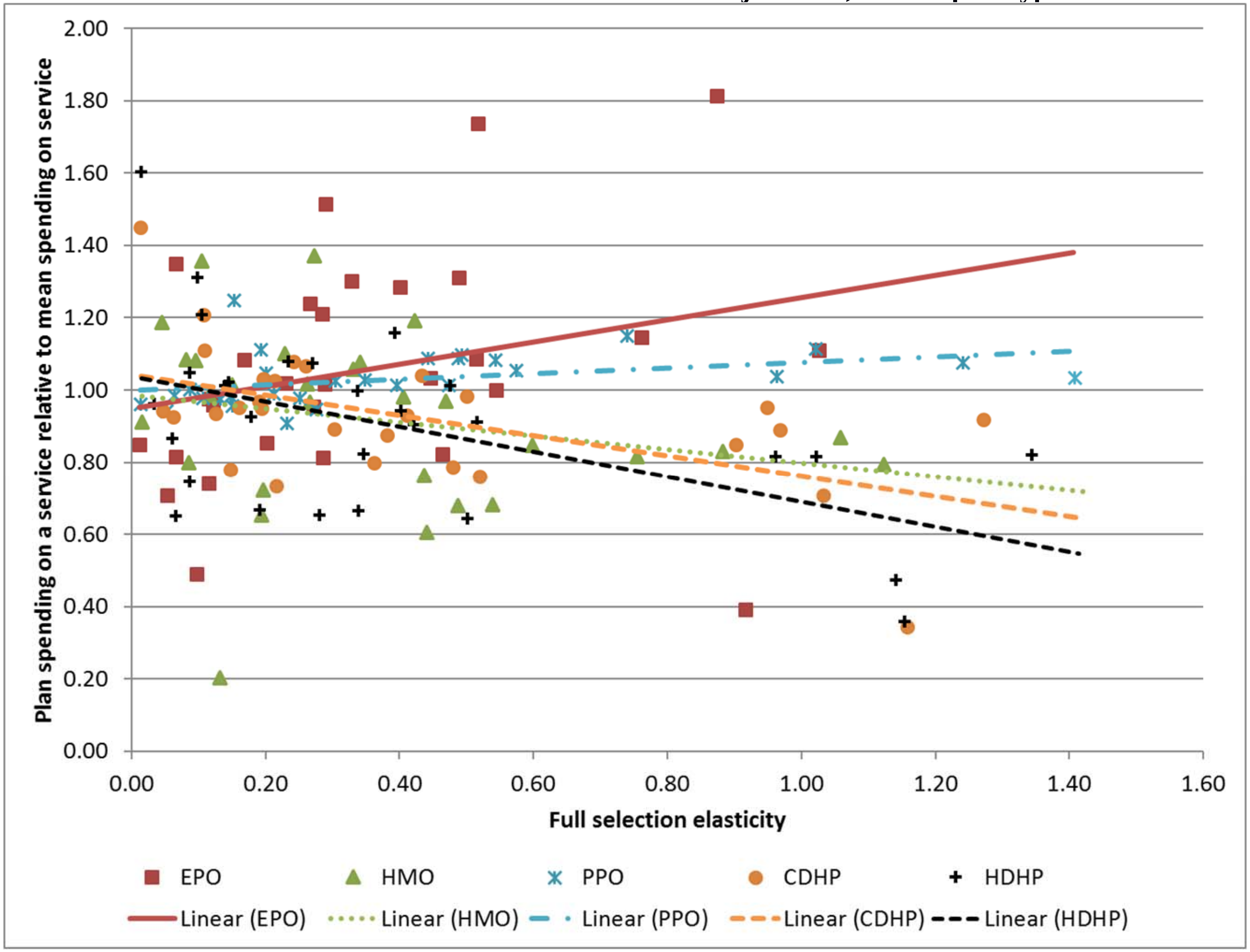
Notes: The FSE for four services are not reported, as the elasticities for these services likely are not well-identified (wrong sign).

Figure 2 – Comparison of weighted average full selection elasticity (FSE) across population subgroups, with no risk adjustment



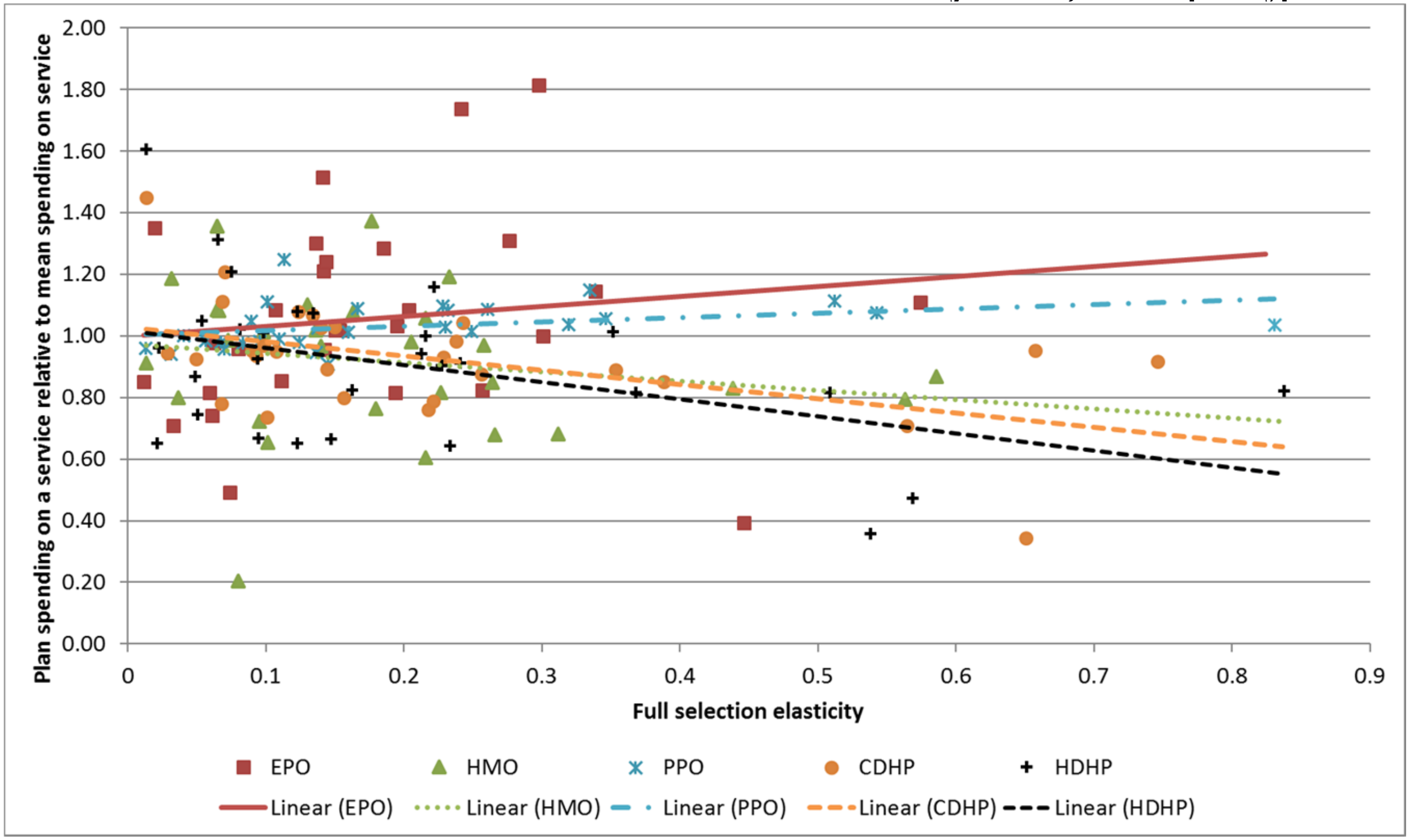
Notes: Each bar presents the spending-weighted average FSE of 29 services recalculated for each population subgroup, as presented in appendix Tables A-4 to A-6. The FSE was recalculated separately for each population subgroup, which implicitly allows premiums to adjust so that profits are zero on average for each calculation. This is plausible for plan type, year, coverage category, and age group, but implausible for RRS intervals. See text for discussion.

Figure 3 – Actual selection versus full selection elasticities with no risk adjustment, for five plan types



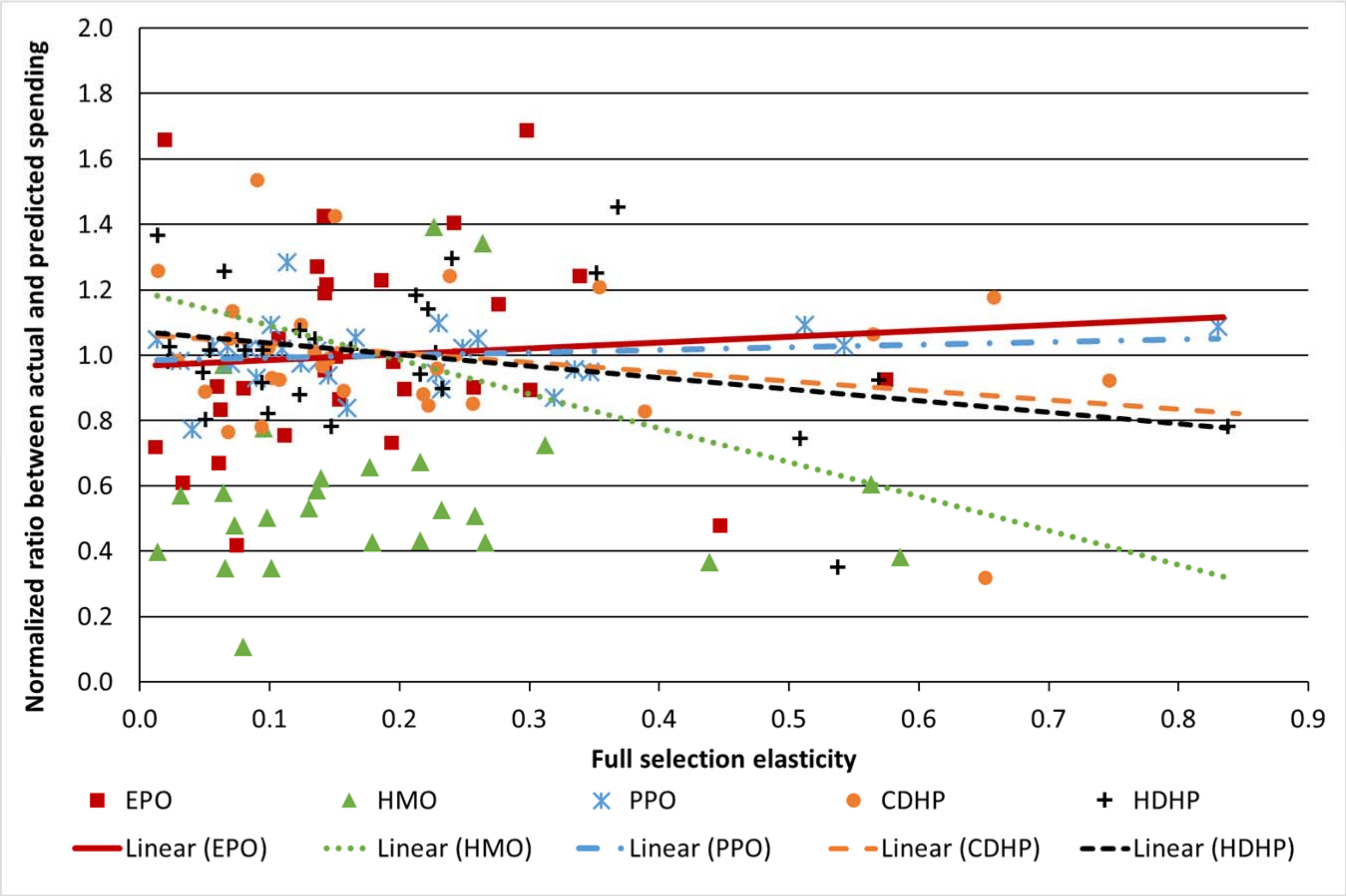
Note: For each of the 29 types of services, the figure plots the ratio between the share of spending by the plan over the overall average share in that service versus the full selection elasticity, without risk adjustment.

Figure 4 – Actual selection versus full selection elasticities with concurrent risk adjustment, for five plan types



Note: For each of the 29 types of services, the figure plots the ratio between the share of spending by the plan over the overall average share in that service versus the full selection elasticity, with concurrent risk adjustment.

Figure 5 – Predictive ratios versus full selection elasticities with concurrent risk adjustment, for five plan types



Note: For each of 29 types of service, the figure plots the ratio between actual and predicted spending using a concurrent risk adjustment model, normalized by the plan's average spending, versus full selection elasticities. The Y-scale is truncated at 2.

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	13,997,319	34.0	18.3	4,355	16,800	3,941	14,231	0.13
By Plan type:								
EPO	94,385	35.3	18.6	4,469	14,619	3,888	11,841	0.08
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	216,391	42.2	18.8	6,300	21,080	5,775	18,343	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 (2016) sample of 13,997,319 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 33 types of service with no risk adjustment

	Mean spending	Mean cost share	Elasticity	CV	$\rho_{\hat{m}_s,\pi}$	EM selection index	Full selection elasticity
All types of spending	4354.56	0.13	-0.33 ***	6.75	-0.5	3.41	1.20
By TOS:							
Non-specialty visits	293.13	0.22	-0.16 ***	3.24	-0.3	0.98	0.24
Home visits	11.54	0.04	-0.004	273.28	-0.11	29.87	0.11
Prevention	50.37	0.04	-0.01 **	2.48	-0.03	0.08	0.01
Maternity	133.61	0.11	-0.06 ***	8.8	-0.02	0.18	0.07
Mental health	103.62	0.21	-0.18 ***	16.31	-0.09	1.54	0.35
Substance abuse	20.32	0.12	-0.05	59.59	-0.04	2.56	0.16
Major surgical procedures	86.49	0.02	0.06	7.11	-0.36	2.59	-0.19
Surgical supplies/devices	56.61	0.02	-0.17 **	6.73	-0.31	2.08	0.49
Nonsurgery IP procs	85.5	0.06	-0.06 **	8.84	-0.32	2.80	0.20
Specialty visits	708.5	0.15	-0.22 ***	4.75	-0.35	1.66	0.49
Dialysis	30.27	0.03	0.02	205.75	-0.19	39.28	-0.54
PT, OT, speech therapy	98.61	0.20	-0.10 ***	8.58	-0.17	1.47	0.20
Chiropractic	25.66	0.35	-0.15 ***	12.8	-0.05	0.62	0.15
Hospice	0.53	0.02	3.92 *	218.09	-0.05	11.06	-44.15
Emergency room	219.51	0.17	-0.03 **	4.65	-0.25	1.14	0.05
Room board - surgical	233.59	0.03	-0.13 *	8.89	-0.37	3.29	0.52
Room board - medical, other	141.86	0.04	-0.07	16.41	-0.32	5.24	0.38
CAT scan	62.76	0.13	-0.10 ***	8.24	-0.3	2.46	0.30
Mammograms	31.31	0.07	-0.07 ***	6.8	-0.1	0.67	0.11
MRIS	73.77	0.16	-0.21 ***	6.13	-0.29	1.75	0.47
PET scans	6.54	0.06	-0.13 **	44.3	-0.16	7.01	0.94
Radiology - diagnostic	71.72	0.17	-0.10 ***	4.29	-0.39	1.66	0.22
Radiology - therapeutic	36.69	0.02	0.05	13.99	-0.26	3.57	-0.21
Ultrasounds	32.27	0.21	-0.10 ***	4.24	-0.2	0.83	0.13
Diagnostic services	116.92	0.13	-0.10 ***	5.32	-0.38	2.00	0.25
Laboratory other	183.15	0.19	-0.11 ***	8.05	-0.3	2.37	0.29
Pharmacy	959.51	0.16	-0.33 ***	12	-0.34	4.02	1.33
Facility-based pharmacy	153.2	0.04	-0.10 ***	24.01	-0.3	7.20	0.76
Specialty drugs, injections	136.74	0.05	-0.05 ***	51.83	-0.25	12.99	0.57
Non-surg supplies/devices	61.29	0.12	-0.18 ***	36.69	-0.17	6.26	1.09
DME	27.36	0.15	-0.12 ***	15.88	-0.22	3.55	0.45
Transportation	23.95	0.09	-0.05	8.13	-0.3	2.46	0.14
Other	83.79	0.06	-0.15 ***	38.03	-0.17	6.38	0.98
ϕ = derivative of profit with respect to expected spending							1.64E-05
σ_π = standard deviation of individual profit							58,196

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 13,997,319 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 types of spending	1.20	1.13	0.70	0.65	0.82	0.48
By TOS:						
Non-specialty visits	0.24	0.22	0.16	0.15	0.20	0.14
Home visits	0.11	0.11	0.07	0.06	0.04	0.01
Prevention	0.01	0.01	0.01	0.01	0.01	0.01
Maternity	0.07	0.07	0.06	0.06	0.07	0.06
Mental health	0.35	0.36	0.24	0.23	0.30	0.23
Substance abuse	0.16	0.16	0.11	0.10	0.12	0.09
Surgical supplies/devices	0.49	0.42	0.25	0.23	0.38	0.22
Nonsurgery IP procs	0.20	0.19	0.10	0.09	0.15	0.08
Specialty visits	0.49	0.44	0.28	0.27	0.39	0.25
PT, OT, speech therapy	0.20	0.18	0.11	0.10	0.17	0.11
Chiropractic	0.15	0.14	0.11	0.11	0.15	0.12
Emergency room	0.05	0.05	0.03	0.03	0.04	0.03
Room board - surgical	0.52	0.47	0.25	0.23	0.35	0.18
Room board - medical, other	0.38	0.36	0.18	0.16	0.23	0.10
CAT scan	0.30	0.28	0.15	0.14	0.22	0.12
Mammograms	0.11	0.08	0.07	0.07	0.11	0.07
MRIS	0.47	0.43	0.26	0.25	0.38	0.25
PET scans	0.94	0.89	0.35	0.31	0.58	0.21
Radiology - diagnostic	0.22	0.19	0.12	0.11	0.17	0.11
Ultrasounds	0.13	0.12	0.09	0.08	0.12	0.09
Diagnostic services	0.25	0.23	0.14	0.13	0.19	0.11
Laboratory other	0.29	0.27	0.16	0.14	0.21	0.12
Pharmacy	1.33	1.25	0.85	0.77	1.01	0.67
Facility-based pharmacy	0.76	0.73	0.39	0.35	0.42	0.18
Specialty drugs, injections	0.57	0.56	0.37	0.34	0.29	0.16
Non-surg supplies/devices	1.09	1.05	0.59	0.50	0.61	0.26
DME	0.45	0.42	0.23	0.18	0.31	0.15
Transportation	0.14	0.13	0.08	0.07	0.10	0.06
Other	0.98	0.94	0.55	0.49	0.55	0.26
Weighted average full selection elasticity	0.56	0.53	0.34	0.31	0.42	0.26
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	58,196	57,621	52,898	40,852	32,291	21,901
Correlation with base case	1	0.999	0.973	0.965	0.969	0.849

Notes: Results use the full sample of single and family enrollees, 2008-14 in 73 identified employers, for a sample of 13,997,319 enrollees continuously eligible for at least three full calendar years with no mid-year plan switching. Not shown are results for five 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						
	EPO	HMO	POS	PPO	Comp	CDHP	HDHP
ALL	1.06	1.03	1.04	1.24	1.59	1.30	1.04
Non-specialty visits	0.23	0.27	0.23	0.23	0.31	0.21	0.14
Home visits	0.07	0.09	0.13	0.09	0.30	0.16	0.07
Prevention	0.01	0.02	0.01	0.01	0.01	0.01	0.01
Maternity	0.07	0.08	0.06	0.06	0.06	0.06	0.06
Mental health	0.29	0.33	0.35	0.35	0.40	0.38	0.34
Substance abuse	0.11	0.10	0.16	0.15	0.11	0.20	0.48
Surgical supplies/devices	0.52	0.44	0.48	0.49	0.52	0.50	0.52
Nonsurgery IP procs	0.28	0.20	0.21	0.20	0.27	0.22	0.19
Specialty visits	0.54	0.49	0.55	0.49	0.61	0.43	0.39
PT, OT, speech therapy	0.20	0.19	0.18	0.19	0.28	0.19	0.15
Chiropractic	0.10	0.13	0.10	0.15	0.20	0.13	0.10
Emergency room	0.05	0.05	0.05	0.05	0.07	0.05	0.03
Room board - surgical	0.40	0.41	0.50	0.54	0.47	0.52	0.50
Room board - medical, other	0.33	0.34	0.34	0.40	0.52	0.36	0.28
CAT scan	0.29	0.27	0.31	0.30	0.35	0.30	0.35
Mammograms	0.12	0.12	0.11	0.11	0.11	0.11	0.10
MRIS	0.49	0.47	0.47	0.47	0.59	0.41	0.42
PET scans	0.87	0.76	0.92	0.96	0.91	0.97	1.02
Radiology - diagnostic	0.27	0.23	0.21	0.21	0.29	0.20	0.18
Ultrasounds	0.17	0.15	0.13	0.13	0.15	0.11	0.09
Diagnostic services	0.27	0.26	0.25	0.25	0.26	0.24	0.23
Laboratory other	0.29	0.42	0.26	0.28	0.36	0.26	0.27
Pharmacy	1.03	1.06	0.99	1.41	1.41	1.27	1.34
Facility-based pharmacy	0.45	0.60	0.87	0.74	1.22	1.03	1.14
Specialty drugs, injections	0.46	0.54	0.39	0.58	0.51	0.95	0.40
Non-surg supplies/devices	0.76	1.12	0.76	1.24	1.35	0.90	0.96
DME	0.51	0.44	0.46	0.44	0.86	0.48	0.34
Transportation	0.11	0.11	0.11	0.15	0.27	0.15	0.09
Other	0.92	0.88	0.70	1.02	0.83	1.16	1.15
Weighted average full selection elasticity	0.46	0.45	0.46	0.60	0.67	0.53	0.49
σ_π = standard deviation of individual profit	50,641	47,776	54,182	61,398	73,024	57,482	53,502
Correlation with base case	0.962	0.981	0.962	0.998	0.943	0.959	0.950

Table 5 – 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	0.74	1.20	2.13	0.46	0.65	1.01
Non-specialty visits	0.18	0.24	0.35	0.14	0.15	0.17
Home visits	0.06	0.11	0.22	0.03	0.06	0.11
Prevention	0.01	0.01	0.02	0.01	0.01	0.01
Maternity	0.06	0.07	0.08	0.06	0.06	0.06
Mental health	0.25	0.35	0.56	0.19	0.23	0.32
Substance abuse	0.10	0.16	0.27	0.07	0.10	0.16
Surgical supplies/devices	0.33	0.49	0.81	0.20	0.23	0.30
Nonsurgery IP procs	0.13	0.20	0.35	0.07	0.09	0.13
Specialty visits	0.34	0.49	0.80	0.23	0.27	0.34
PT, OT, speech therapy	0.14	0.20	0.31	0.09	0.10	0.12
Chiropractic	0.12	0.15	0.21	0.10	0.11	0.12
Emergency room	0.04	0.05	0.08	0.03	0.03	0.04
Room board - surgical	0.32	0.52	0.91	0.18	0.23	0.33
Room board - medical, other	0.22	0.38	0.70	0.11	0.16	0.25
CAT scan	0.20	0.30	0.52	0.12	0.14	0.19
Mammograms	0.09	0.11	0.15	0.07	0.07	0.07
MRIS	0.33	0.47	0.77	0.21	0.25	0.32
PET scans	0.53	0.94	1.76	0.22	0.31	0.50
Radiology - diagnostic	0.15	0.22	0.35	0.10	0.11	0.14
Ultrasounds	0.10	0.13	0.19	0.08	0.08	0.10
Diagnostic services	0.17	0.25	0.42	0.11	0.13	0.17
Laboratory other	0.19	0.29	0.49	0.11	0.14	0.19
Pharmacy	0.80	1.33	2.38	0.52	0.77	1.26
Faciliity-based pharmacy	0.43	0.76	1.43	0.22	0.35	0.60
Specialty drugs, injections	0.31	0.57	1.11	0.19	0.34	0.64
Non-surg supplies/devices	0.62	1.09	2.03	0.33	0.50	0.84
DME	0.28	0.45	0.80	0.14	0.18	0.26
Transportation	0.09	0.14	0.24	0.06	0.07	0.10
Other	0.56	0.98	1.81	0.31	0.49	0.84
Weighted average full selection elasticity	0.35	0.56	0.99	0.23	0.31	0.48
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	58,196	58,196	58,196	40,852	40,852	40,852
Correlation with base case	0.995	1	0.9980	0.986	1	0.992

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 $\rho_{\hat{m}_s,\pi}$	EM selection index	Full selection elasticity
ALL	-0.33	4,355	29,375	0.25	6.75	-0.5	3.41	1.20
Non-specialty visits	-0.16	293	950	0.1	3.24	-0.3	0.98	0.24
Home visits	-0.004	12	3,153	0.69	273.28	-0.11	29.87	0.11
Prevention	-0.01	50	125	0.21	2.48	-0.03	0.08	0.01
Maternity	-0.06	134	1,175	0.04	8.8	-0.02	0.18	0.07
Mental health	-0.18	104	1,691	0.13	16.31	-0.09	1.54	0.35
Substance abuse	-0.05	20	1,211	0.12	59.59	-0.04	2.56	0.16
Surgical procedures	0.06	86	615	0.01	7.11	-0.36	2.59	-0.19
Surgical supplies/devices	-0.17	57	381	0.01	6.73	-0.31	2.08	0.49
Nonsurgery IP procs	-0.06	86	756	0.03	8.84	-0.32	2.8	0.20
Specialty visits	-0.22	709	3,363	0.09	4.75	-0.35	1.66	0.49
Dialysis	0.01	30	6,228	0.49	205.75	-0.19	39.28	-0.54
PT, OT, speech therapy	-0.10	99	847	0.14	8.58	-0.17	1.47	0.20
Chiropractic	-0.15	26	329	0.41	12.8	-0.05	0.62	0.15
Hospice	3.92	1	116	0.09	218.09	-0.05	11.06	-44.15
Emergency room	-0.03	220	1,020	0.06	4.65	-0.25	1.14	0.05
Room board - surgical	-0.13	234	2,076	0.01	8.89	-0.37	3.29	0.52
Room board - medical, other	-0.07	142	2,328	0.04	16.41	-0.32	5.24	0.38
CAT scan	-0.10	63	517	0.07	8.24	-0.3	2.46	0.30
Mammograms	-0.07	31	213	0.28	6.8	-0.1	0.67	0.11
MRIS	-0.21	74	452	0.08	6.13	-0.29	1.75	0.47
PET scans	-0.13	7	290	0.17	44.3	-0.16	7.01	0.94
Radiology - diagnostic	-0.10	72	308	0.03	4.29	-0.39	1.66	0.22
Radiology - therapeutic	0.05	37	513	0.01	13.99	-0.26	3.57	-0.21
Ultrasounds	-0.09	32	137	0.04	4.24	-0.2	0.83	0.13
Diagnostic services	-0.10	117	622	0.03	5.32	-0.38	2	0.25
Laboratory other	-0.11	183	1,474	0.17	8.05	-0.3	2.37	0.29
Pharmacy	-0.33	960	11,514	0.61	12	-0.34	4.02	1.33
Facility-based pharmacy	-0.10	153	3,678	0.1	24.01	-0.3	7.2	0.76
Specialty drugs, injections	-0.05	137	7,087	0.34	51.83	-0.25	12.99	0.57
Non-surg supplies/devices	-0.18	61	2,249	0.25	36.69	-0.17	6.26	1.09
DME	-0.12	27	435	0.11	15.88	-0.22	3.55	0.45
Transportation	-0.05	24	195	0.01	8.13	-0.3	2.46	0.14
Other	-0.15	84	3,187	0.25	38.03	-0.17	6.38	0.98
Weighted average full selection elasticity								0.56
ϕ = derivative of profit with respect to expected spending								1.64E-05
σ_π = standard deviation of individual profit								58,196

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	-0.47	3.17	1.13	-0.25	1.71	0.70	-0.28	1.90	0.65
Non-specialty visits	-0.26	0.85	0.22	-0.10	0.31	0.16	-0.10	0.32	0.15
Home visits	-0.11	30.05	0.11	-0.08	21.50	0.07	-0.08	20.79	0.06
Prevention	-0.01	0.04	0.01	0.00	0.01	0.01	0.00	0.01	0.01
Maternity	-0.02	0.18	0.07	0.00	0.03	0.06	0.00	0.01	0.06
Mental health	-0.10	1.58	0.36	-0.05	0.80	0.24	-0.06	0.92	0.23
Substance abuse	-0.04	2.64	0.16	-0.03	1.63	0.11	-0.03	1.93	0.10
Surgical procedures	-0.32	2.25	-0.17	-0.12	0.86	-0.10	-0.13	0.90	-0.09
Surgical supplies/devices	-0.25	1.69	0.42	-0.09	0.60	0.25	-0.09	0.60	0.23
Nonsurgery IP procs	-0.28	2.48	0.19	-0.11	0.98	0.10	-0.11	1.01	0.09
Specialty visits	-0.29	1.39	0.44	-0.12	0.56	0.28	-0.12	0.58	0.27
Dialysis	-0.19	39.27	-0.54	-0.12	23.77	-0.30	-0.14	29.50	-0.29
PT, OT, speech therapy	-0.15	1.25	0.18	-0.05	0.39	0.11	-0.04	0.38	0.10
Chiropractic	-0.03	0.43	0.14	-0.01	0.15	0.11	-0.01	0.18	0.11
Hospice	-0.05	10.68	-42.41	-0.02	4.21	-17.79	-0.02	4.56	-15.50
Emergency room	-0.23	1.08	0.05	-0.09	0.42	0.03	-0.09	0.43	0.03
Room board - surgical	-0.33	2.93	0.47	-0.13	1.17	0.25	-0.14	1.22	0.23
Room board - medical, other	-0.30	5.00	0.36	-0.13	2.10	0.18	-0.13	2.18	0.16
CAT scan	-0.27	2.19	0.28	-0.09	0.78	0.15	-0.10	0.82	0.14
Mammograms	-0.02	0.17	0.08	-0.01	0.04	0.07	-0.01	0.04	0.07
MRIS	-0.25	1.52	0.43	-0.09	0.56	0.26	-0.10	0.62	0.25
PET scans	-0.15	6.61	0.89	-0.05	2.16	0.35	-0.05	2.28	0.31
Radiology - diagnostic	-0.32	1.37	0.19	-0.12	0.52	0.12	-0.12	0.53	0.11
Radiology - therapeutic	-0.22	3.06	-0.19	-0.07	1.02	-0.09	-0.08	1.10	-0.08
Ultrasounds	-0.14	0.60	0.12	-0.05	0.21	0.09	-0.05	0.21	0.08
Diagnostic services	-0.33	1.74	0.23	-0.13	0.67	0.14	-0.13	0.69	0.13
Laboratory other	-0.26	2.13	0.27	-0.11	0.87	0.16	-0.11	0.88	0.14
Pharmacy	-0.31	3.76	1.25	-0.20	2.40	0.85	-0.22	2.68	0.77
Faciliity-based pharmacy	-0.29	6.93	0.73	-0.14	3.45	0.39	-0.16	3.90	0.35
Specialty drugs, injections	-0.25	12.77	0.56	-0.17	8.68	0.37	-0.20	10.40	0.34
Non-surg supplies/devices	-0.16	6.05	1.05	-0.09	3.18	0.59	-0.09	3.27	0.50
DME	-0.21	3.29	0.42	-0.09	1.42	0.23	-0.07	1.14	0.18
Transportation	-0.28	2.30	0.13	-0.12	0.95	0.08	-0.12	0.96	0.07
Other	-0.16	6.16	0.94	-0.09	3.43	0.55	-0.10	3.81	0.49
Weighted average full selection elasticity			0.53			0.34			0.31
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			57,621			52,898			40,852

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	-0.53	3.56	0.82	-0.29	1.96	0.48
Non-specialty visits	-0.36	1.17	0.20	-0.15	0.49	0.14
Home visits	-0.08	20.56	0.04	-0.03	7.63	0.01
Prevention	-0.06	0.16	0.01	-0.03	0.07	0.01
Maternity	-0.04	0.33	0.07	-0.02	0.15	0.06
Mental health	-0.13	2.05	0.30	-0.10	1.70	0.23
Substance abuse	-0.05	2.91	0.12	-0.04	2.57	0.09
Surgical procedures	-0.40	2.86	-0.14	-0.15	1.03	-0.08
Surgical supplies/devices	-0.38	2.54	0.38	-0.14	0.96	0.22
Nonsurgery IP procs	-0.35	3.09	0.15	-0.13	1.18	0.08
Specialty visits	-0.42	1.98	0.39	-0.17	0.82	0.25
Dialysis	-0.12	25.20	-0.20	-0.05	9.36	-0.06
PT, OT, speech therapy	-0.23	1.96	0.17	-0.10	0.90	0.11
Chiropractic	-0.08	1.04	0.15	-0.05	0.64	0.12
Hospice	-0.05	11.30	-26.70	-0.02	4.66	-10.22
Emergency room	-0.29	1.33	0.04	-0.14	0.64	0.03
Room board - surgical	-0.38	3.42	0.35	-0.13	1.13	0.18
Room board - medical, other	-0.31	5.02	0.23	-0.10	1.69	0.10
CAT scan	-0.33	2.73	0.22	-0.12	0.99	0.12
Mammograms	-0.16	1.09	0.11	-0.03	0.17	0.07
MRIS	-0.36	2.19	0.38	-0.17	1.07	0.25
PET scans	-0.16	7.01	0.58	-0.04	1.95	0.21
Radiology - diagnostic	-0.45	1.95	0.17	-0.17	0.73	0.11
Radiology - therapeutic	-0.28	3.94	-0.15	-0.09	1.25	-0.07
Ultrasounds	-0.27	1.14	0.12	-0.10	0.42	0.09
Diagnostic services	-0.43	2.28	0.19	-0.17	0.89	0.11
Laboratory other	-0.32	2.54	0.21	-0.11	0.91	0.12
Pharmacy	-0.42	5.07	1.01	-0.34	4.06	0.67
Faciliity-based pharmacy	-0.26	6.32	0.42	-0.10	2.44	0.18
Specialty drugs, injections	-0.21	10.97	0.29	-0.14	7.45	0.16
Non-surg supplies/devices	-0.15	5.42	0.61	-0.05	1.91	0.26
DME	-0.24	3.86	0.31	-0.09	1.37	0.15
Transportation	-0.31	2.51	0.10	-0.11	0.92	0.06
Other	-0.15	5.61	0.55	-0.07	2.54	0.26
Weighted average full selection elasticity			0.42			0.26
ϕ = derivative of profit with respect to expected spending			1.64E-05			1.64E-05
σ_π = standard deviation of individual profit			32,291			21,901

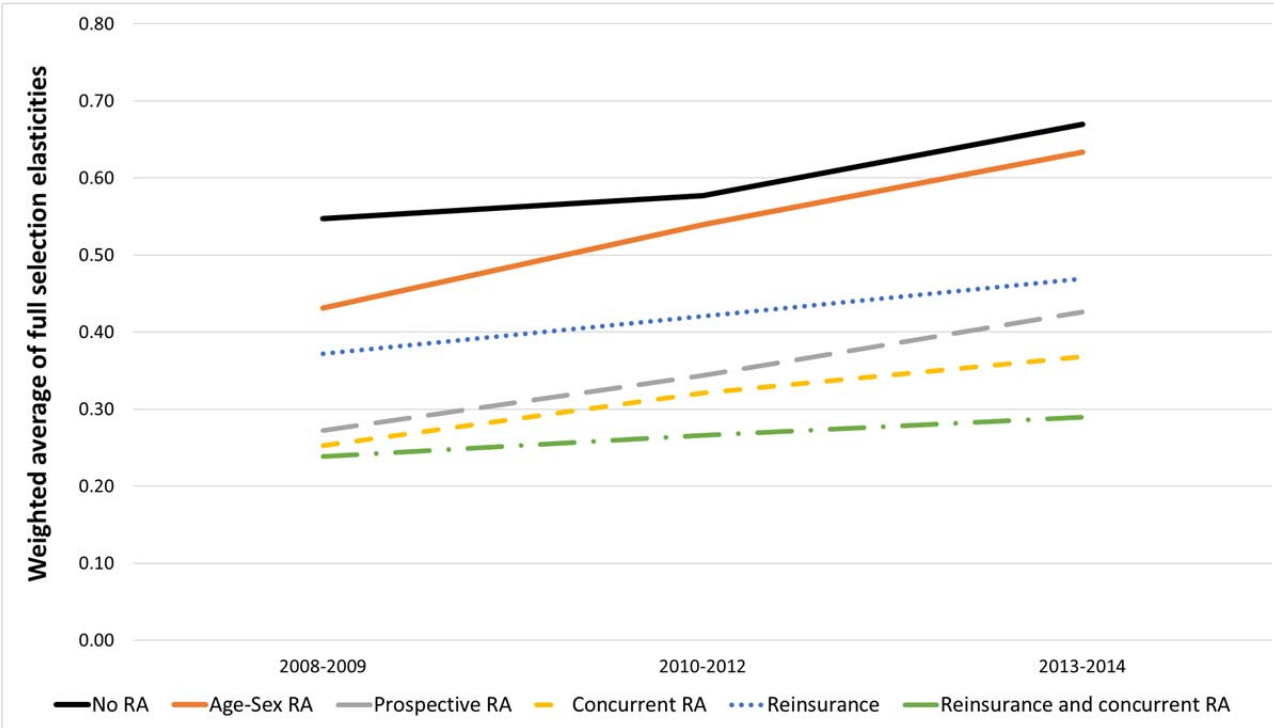
Table A-4 – Comparison of full selection elasticities across subgroups: year groups and family type – No risk adjustment

	Year groups			Single/family coverage	
	2008-2009	2010-2012	2013-2014	Single	Family
ALL	1.16	1.22	1.44	1.17	1.21
Non-specialty visits	0.28	0.24	0.26	0.25	0.23
Home visits	0.07	0.11	0.14	0.06	0.12
Prevention	0.01	0.01	0.01	0.02	0.01
Maternity	0.07	0.07	0.07	0.06	0.07
Mental health	0.41	0.35	0.38	0.34	0.36
Substance abuse	0.12	0.11	0.24	0.12	0.16
Surgical supplies/devices	0.45	0.49	0.56	0.44	0.50
Nonsurgery IP procs	0.19	0.21	0.25	0.18	0.21
Specialty visits	0.51	0.50	0.54	0.51	0.48
PT, OT, speech therapy	0.22	0.19	0.22	0.19	0.19
Chiropractic	0.23	0.15	0.13	0.14	0.16
Emergency room	0.05	0.05	0.05	0.05	0.05
Room board - surgical	0.51	0.50	0.61	0.47	0.53
Room board - medical, other	0.40	0.36	0.44	0.33	0.40
CAT scan	0.29	0.31	0.38	0.30	0.30
Mammograms	0.12	0.11	0.11	0.11	0.11
MRIS	0.50	0.47	0.53	0.46	0.47
PET scans	0.83	0.94	1.15	0.86	0.97
Radiology - diagnostic	0.24	0.22	0.25	0.22	0.21
Ultrasounds	0.16	0.14	0.13	0.13	0.13
Diagnostic services	0.26	0.25	0.29	0.24	0.26
Laboratory other	0.29	0.29	0.35	0.26	0.29
Pharmacy	1.18	1.39	1.68	1.20	1.37
Facility-based pharmacy	0.61	0.80	1.11	0.74	0.77
Specialty drugs, injections	0.61	0.62	0.54	0.46	0.63
Non-surg supplies/devices	0.84	1.16	1.66	1.28	1.04
DME	0.50	0.46	0.46	0.36	0.49
Transportation	0.13	0.13	0.18	0.14	0.14
Other	0.67	1.06	2.05	0.96	0.98
Weighted average full selection elasticity	0.55	0.58	0.67	0.55	0.57
σ_π = standard deviation of individual profit	54,199	61,678	68,296	64,250	56,509
Correlation with base case	0.977	0.999	0.953	0.987	0.999

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	1.43	1.40	1.03	1.17	0.33	0.38	0.52	2.62
Non-specialty visits	0.20	0.19	0.21	0.26	0.13	0.13	0.15	0.50
Home visits	0.21	0.22	0.10	0.05	0.01	0.01	0.02	0.13
Prevention	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
Maternity	0.14	0.07	0.08	0.06	0.06	0.05	0.05	-0.06
Mental health	0.73	0.35	0.35	0.35	0.19	0.22	0.27	0.47
Substance abuse	0.48	0.18	0.17	0.13	0.06	0.09	0.17	0.17
Surgical supplies/devices	1.32	0.43	0.42	0.44	0.18	0.18	0.20	0.47
Nonsurgery IP procs	0.40	0.30	0.19	0.17	0.06	0.06	0.07	0.30
Specialty visits	0.52	0.37	0.42	0.48	0.21	0.21	0.25	0.87
PT, OT, speech therapy	0.41	0.19	0.15	0.19	0.09	0.10	0.10	0.25
Chiropractic	0.14	0.13	0.14	0.14	0.12	0.11	0.11	0.03
Emergency room	0.03	0.04	0.05	0.06	0.02	0.03	0.03	0.12
Room board - surgical	1.40	0.78	0.47	0.44	0.14	0.14	0.16	0.78
Room board - medical, other	0.43	0.61	0.34	0.33	0.07	0.07	0.10	0.58
CAT scan	0.32	0.19	0.24	0.32	0.10	0.10	0.12	0.52
Mammograms	0.05	0.08	0.09	0.08	0.08	0.07	0.07	0.04
MRIS	0.98	0.40	0.40	0.46	0.19	0.20	0.24	0.68
PET scans	1.25	1.09	0.94	0.88	0.14	0.15	0.22	1.09
Radiology - diagnostic	0.24	0.17	0.18	0.21	0.09	0.09	0.10	0.35
Ultrasounds	0.18	0.13	0.12	0.13	0.08	0.08	0.09	0.18
Diagnostic services	0.36	0.27	0.22	0.23	0.09	0.10	0.11	0.41
Laboratory other	0.36	0.42	0.22	0.28	0.10	0.10	0.13	0.69
Pharmacy	1.07	2.21	1.18	1.14	0.43	0.50	0.69	2.21
Facility-based pharmacy	0.67	0.72	0.79	0.74	0.11	0.12	0.20	1.25
Specialty drugs, injections	0.65	1.42	0.59	0.46	0.06	0.12	0.29	0.79
Non-surg supplies/devices	1.89	0.90	0.75	1.32	0.17	0.19	0.23	2.17
DME	1.82	0.86	0.34	0.36	0.11	0.12	0.14	0.64
Transportation	0.55	0.09	0.11	0.14	0.04	0.05	0.06	0.32
Other	4.19	1.15	0.92	0.76	0.18	0.18	0.31	2.11
Weighted average full selection elasticity	0.57	0.73	0.46	0.54	0.17	0.22	0.29	1.03
σ_π = standard deviation of individual profit	49,067	42,173	48,425	74,861	28,737	48,189	72,357	219,521
Correlation with base case	0.688	0.893	0.982	0.976	0.761	0.781	0.833	0.958

Figure A-1 – Evolution of weighted average of full selection elasticities for 29 services 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, $\eta_{is} = \eta_s^j \ \forall\ i \in j = 1,2,\dots,J$.

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

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

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

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

The full selection elasticity becomes, then:

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

$$= \sum_{j=1}^{J} FSE^j \times \frac{N^j \bar{m}_s^j}{N\bar{m}_s} \tag{A1}$$

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 (A1) shows that it is only relevant insofar those consumers have enough medical consumption as a fraction of the total. Equation (A1) 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 (7), given by the individual 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 form by individuals' characteristics.