Demand Elasticities and Service Selection Incentives among Competing Private Health Plans

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Abstract: We examine both the incentive to select 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 profits and demand elasticities across 33 disaggregated types of service. Using privately-insured claims data from 73 large employers from 2007 to 2014, we address three questions. Are service-level selection incentives and actual service distortions getting better or worse over time? How well does concurrent rather than prospective risk adjustment reduce selection incentives, and how do they compare to reinsurance as an alternative? And finally, do the three newly-popular health plan types: exclusive provider organizations (EPOs), consumer driven health plans (CDHP), and high deductible health plans (HDHP) risk select more or less than Health Maintenance Organization (HMO) and Preferred Provider Organization (PPO) plans?

We find that incorporating demand responsiveness and profit variation meaningfully changes which services have the strongest incentive for underprovision. Selection incentives are getting stronger over time. Prospective diagnosis-based risk adjusted premiums reduces selection incentives by about 40% relative to premiums that are not risk-adjusted, while concurrent diagnosis based risk adjustment reduces selection incentives by about 45%, suggesting that even though their R^2 is much higher, concurrent risk adjustment has only a modest superiority on overall selection incentives over prospective risk adjustment. Reinsurance at 80 percent of patient cost over \$60,000 reduces selection incentives by about 25%. This last result occurs because while reinsurance significantly reduces the variability of individual level profits, it increases the correlations of expected spending with profits, making selection incentives stronger. This higher correlation dominates the effect of the reduction in overall profit variation. In our sample, CHDH and HDHP, along with HMOs, show strong evidence of selection, while EPOs are similar to PPOs in their much lower level of actual selection.

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

Introduction

Fixed premiums create strong profit incentives for health plans to prefer enrolling healthy, low-cost rather than sicker, high-cost enrollees, since premiums never 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 the supply-side availability of specific types of providers or type of services, which can be manipulated by health plans to influence individual enrollment decisions. Service level selection is also easy when health plans can use demand-side incentives and design benefit plan cost sharing to attract or deter enrollees expecting to use certain 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 improve the empirical measure of the service level selection incentives by incorporating new information about service-level demand elasticities, individual-level profit variation, and demand for health insurance in the calculation. Second, we update the two previous studies that have quantified incentives for service level selection using larger and richer data, and assess whether both the incentive to select and the magnitude of actual selection are getting better or worse over time. Third, we calculate empirically how well three regulatory strategies reduce selection incentives: prospective risk adjustment, concurrent risk adjustment and individual-level reinsurance. Finally, we examine not only the incentive to select but the reality of it in seven health plan types, notably including three newly-popular plan types, that restrict access to certain providers using either supply- or demand-side incentives.

The seminal theory paper worrying about service level selection in competitive health plan markets is Glazer and McGuire (2000), which demonstrates how to calculate 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. Ellis and McGuire (2007) (henceforth EM) make further progress by deriving a selection index that is easy to implement empirically. The EM selection index is the product of two measures --- 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). EM demonstrate that these two concepts correspond analytically to two empirical measures: the coefficient of variation of expected spending on a service (predictability), and the correlation between expected spending on a service and individual level profits (predictiveness). EM use Medicare data to calculate selection indices that are the product of predictability and predictiveness and find that services such as hospice care, home health care and durable medical equipment have incentives to be the most tightly controlled (i.e., underprovided), while services such as eye procedures and magnetic resonance imaging have the strongest incentives to be overprovided under capitated payment. EM do not actually show that plans behave as predicted by their model, only establish that they have an incentive to do so.[1]

Ellis, Jiang and Kuo (2013) (henceforth EJK) was the first paper to actually examine the predictions of the EM selection index framework empirically. Using the 2003 and 2004

[1] Many other empirical studies demonstrate 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 actually 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.

MarketScan commercial claims and encounters data, they not only estimate selection incentives on a sample that include both capitated and non-capitated enrollees, but they also test the predictions of this literature by examining whether the services identified as profitable to over- (or under-) supply are actually the ones over (or under) supplied in practice by capitated health plans. They also examine whether prospective, diagnosis-based risk adjustment reduces these service distortion incentives. They find that the EM selection index is robust across different plan types, that risk adjustment reduces the marginal profit of service level selection by approximately 50 percent, and that not only are health maintenance organizations (HMOs) predicted to undersupply certain services, but the empirical evidence suggests that they in fact do so.

In a recent paper Layton, Ellis, and McGuire (2015) (henceforth LEM) develop an alternative measure of service level selection incentives. They separately develop indices of efficient premiums, efficient payment, and efficient service selection. The framework used in their metric for service selection is similar to the EM index, except that LEM characterizes optimal service levels in quantity terms rather than shadow prices. Hence while they characterize welfare maximizing choices using the derivative of profits and benefits with respect to quantity choices, we follow EM and characterize it in terms of shadow price choices.

One weakness of EM and EJK is that although the formula underlying their selection index identifies five terms that affect incentives to distort services, both studies calculate empirically only two of those terms. Our study is the first study to incorporate empirical estimates of (1) service-level demand elasticities, (2) individual-level profit variation, and (3) demand responsiveness of health insurance enrollment to expected spending in the calculation of profitability incentives from service level selection. We show below how these three terms interact with the EM predictability and predictiveness terms and can affect the magnitude and relative importance of selection incentives across services and alternative payment systems. Service-level demand elasticities were ignored in the EM selection index largely due to a lack of the empirical evidence that could be readily incorporated into their calculation. Here, we take advantage of the results in a new working paper by Ellis, Martins and Zhu (2016) (henceforth EMZ) which develops 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 (HDHP) and consumer-driven health plans (CDHP) where costs 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. By using claims for a very large sample of 14 million people, with over 700 employer*plan*years of information, they are able to relatively precisely estimate elasticities at the level of disaggregated type of service. As discussed below, their method is not perfect, in that the variation in cost sharing is too small to estimate these demand elasticities reliably for very expensive procedures and types of services (inpatient surgery, dialysis, hospice, room and board expenses) these are also services where cost sharing in virtually all plans drops to essentially zero for very high cost enrollees. This paper moves our understanding of selection incentives forward, even if there remains more work to be done on certain types of service.

To give a preview of our results, we find that incorporating demand responsiveness and profit variation into our calculation makes meaningful changes in which services have the strongest incentive for underprovision. We show that even over our seven year sample period there is evidence that selection incentives are growing worse. Prospective diagnosis-based risk adjusted premiums reduces selection incentives by about 40% relative to premiums that are not risk-adjusted, while concurrent diagnosis based risk adjustment reduces selection incentives by about 45%, suggesting that even though their R^2 is much higher, concurrent risk adjustment has only a modest superiority on overall selection incentives over prospective risk adjustment. Reinsurance at 80 percent of patient cost over $60,000 reduces selection incentives by about 25%, less than either prospective or concurrent risk adjustment. This last result, which we did not expect, occurs because while reinsurance significantly reduces the variability of individual level profits, it increases the correlations of expected spending with profits, making selection incentives stronger. This second effect appears to dominate the reduction in overall profit variation in our formulation. We also document that HDHPs and CDHPs are similar to HMOs and show signs of significant selection distortions in the services they provide (although probably influenced by demand rather than supply side plan features), while in our sample the EPOs are similar to the PPOs in their selection incentives and spending patterns.

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 to what we call the Full Selection Elasticity (FSE) to re-estimate selection level incentives in the new sample. The data used in this study is summarized in Section III. Section IV describes the estimation strategy. Section V presents the 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 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 particularly of concern with managed care health plans, since their closer involvement in selecting providers with whom to contract and specifying the constraints under which providers work gives them greater ability to influence the services that are over or undersupplied relative to non-managed care plans. 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.

In the last ten years in particular, there has been 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 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.

In order to reduce selection problems, it is common in the US and elsewhere to adopt regulatory or payment strategies that change incentives. One approach is "risk adjustment" so that the capitated payment (which can be thought of as a premium per month or year) better reflects the expected cost of a given plan's enrollees. The most common form of risk adjustment used in the US and elsewhere is diagnosis-based risk adjustment, whereby diagnostic information is combined with selected demographic variables to predict annual spending, and used to reallocate money between competing health plans. Two forms of risk adjustment are typically used. The prospective models use only information prior to the start of the prediction period, while in concurrent models information is used to predict spending in the same period that such information is available (Ash et al. 2000). These diagnosis-based models have been shown to have a substantially higher predictive power than the demographic only models such as the ones using age and gender only (for a review, see 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 to use reinsurance, whereby insurers are fully or partially insured against the risk of covering individuals who are extremely expensive. The Medicare Part D prescription drug program uses reinsurance, 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.

A valid concern about our use of the MarketScan sample of privately insured health plans to study selection incentives and the magnitude of actual selection distortions is that incentives under employment-based insurance will 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 already found that incentives to select are very similar across plan types, so the incentives are there, it 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 or more health plans. 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 have to have such choice in order for selection incentives to still matter. Finally, even a health plan offering multiple health plan types may negotiate different profit incentives for different plans. For example the insurer may arrange for the PPO plan to be an administrative-services-only plan (with very weak selection incentives), while the HMO products may be at-risk and hence have strong selection incentives. We present evidence below that responsiveness to selection incentives varies at the plan type level in ways that are consistent with the incentives. We find this interesting to document, even if the actual incentives are not perfectly observable to us.

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

Our estimation is based on the Ellis-McGuire (2007) selection index, which we re-derive here for two reasons. (A more complete derivation is presented in the appendix.) One reason for redoing this here is that we want to highlight the role of service level elasticities of demand, η_s ,which are assumed constant in the original EM and EJK formulations. Secondly, we also will be empirically examining payment systems in which the standard deviation of individual level profitability, σ_π, can vary with risk adjustment or reinsurance. As we show below, this profit variation can affect both the magnitude and the rank ordering of the selection incentives across services, and hence is important when comparing selection incentives across different payment programs such as risk adjustment and reinsurance.

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. Assume that there are S services offered by the 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 $\hat{m}_i = \left\{\hat{m}_{i1}, \hat{m}_{i2}, ..., \hat{m}_{iS}\right\}$. The benefit to individual i from a plan is $u_i(\hat{m}_i) = v_i(\hat{m}_i) + \mu_i$, where μ_i is a random term with distribution function Φ_i. Utility from services is assumed to be additively separable, and hence it can be written as $v_i(\hat{m}_i) = \sum_s v_{is}(\hat{m}_{is})$, which implies that all cross price effects are zero.

Individual i chooses this plan if $\mu_i > \bar{\mu}_i - v_i(\hat{m}_i)$, 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 service-specific shadow price a plan sets for service s. The efficient quantity of services for the patient to expect, $\hat{m}_{is}$, will satisfy $v_{is}^{'}(\hat{m}_i) = q_s$.

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

$$\pi(q) = \sum_i n_i(\hat{m}_i(q)) \left[r_i - \sum_s m_{is}(q_s) \right], \tag{1}$$

where r_i is the revenue the plan receives for each individual and $n_i(\hat{m}_i) = 1 - \Phi_i(\bar{\mu}_i - v_i(\hat{m}_i))$ is the probability that health plan expects individual i would choose the plan. All individuals are assumed to share the same elasticity of demand for any service but elasticities can differ across services. Also the demand curve for insurance is assumed to be locally linear, or equivalently the enrollment function is assumed to be locally uniform for all i, so that $\Phi_i' = \phi$.[2]

The derivative of profit with respect to q_s is

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

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

$$= \eta_s(\phi \sum_i \widehat{m}_{is} \pi_i - N \bar{m}_s) \tag{2}$$

[2] Our hope is to relax this assumption in future empirical work, but this is the assumption used in FGM, EM, EJK, and LEM, which we continue here.

where $\eta_s \equiv \frac{q_s \hat{m}'_{is}}{\hat{m}_{is}} = \frac{q_s m'_{is}}{m_{is}}$. Also $N\bar{m}_s = \sum_i n_i m_{is}$, where $\bar{m}_s$ is the average spending on service s, and N is the total number of people in the plan. Also assumed in (2) is that plans have rationed services optimally, so that at the first best $q_s = 1$.

Derivation of the EM selection index, I_s, starts by deriving a formula for what we call here the full selection elasticity (FSE) for service 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:

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

$$= \eta_s(\phi \sum_i \frac{\hat{m}_{is}\pi_i}{N\bar{m}_s} - 1) \qquad (3)$$

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. If a consumer is profitable, then increasing $\hat{m}_{is}$ will increase profits, while if individual profits are negative, decreasing $\hat{m}_{is}$ will improve profits.

To convert the FSE_s expression to a correlation and a standard deviation, define the correlation coefficient $\rho_{\hat{m}_s,\pi} = \frac{\sum_i \hat{m}_{is}\pi_i - N\bar{m}_s\bar{\pi}}{N\sigma_{\hat{m}_s}\sigma_\pi}$ where $\bar{m}_s = \frac{\sum_i n_i \hat{m}_{is}}{N}$ and $\bar{\pi} = \frac{\sum_i n_i \pi_i}{N}$. We can then rewrite the full selection elasticity as:

$$FSE_s = \eta_s(\rho_{\hat{m}_s,\pi}\phi \frac{\sigma_{\hat{m}_s}\sigma_\pi}{\bar{m}_s} + \phi\bar{\pi} - 1) \qquad (4)$$

If we assume that competition among many plans, while not eliminating the incentive to distort services, does drive profits down to zero, then $\bar{\pi} = 0$, and the full selection elasticity can be written as:

$$FSE_s = \eta_s(\sigma_\pi \phi \frac{\sigma_{\hat{m}_s}}{\bar{m}_s} \rho_{\hat{m}_s,\pi} - 1) \qquad (5)$$

Note that expression (5) is a unit free measure consistent with the original definition of FSE_s as an elasticity. The formula contains five terms. The two terms highlighted in EM are "predictability" $\frac{\sigma_{\hat{m}_s}}{\bar{m}_s}$, 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 three other terms – (1) η_s, the demand elasticity for service s, (2) σ_π, the standard deviation of individual level profits, and (3) ϕ, the density of distribution of individual specific valuation of health insurance – are constant across services and were assumed in EM and EJK to change only the magnitude but not the order of rank in the selection index.[3]

In this paper we demonstrate that these three terms can 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.

The demand elasticity can vary across services. As an example of how price elasticities of demand can vary across services, Duarte (2011) estimates price elasticity 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 (2015) estimated price elasticities of demand by taking advantage of a large exogenous change in cost sharing before and after a large 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

[3] 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.

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 (2016), 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. [4]

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 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

[4] 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.

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. σ_π, standard deviation of profits can be readily calculated from the data.[5] The demand elasticities for service s, η_s, use the 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, $\frac{\partial n_i}{\partial M_i}$ or even more ambitiously $\frac{\partial n_i}{\partial m_{is}}$, 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 in more detail how we construct a measure to capture 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, and prospective diagnosis-based risk adjustment, and concurrent diagnosis-based risk adjustment. We also contrast risk adjustment with a simple reinsurance program in the absence of any risk adjustment. To focus the analysis on the differences in incentives between risk adjustment and reinsurance, we examine only a reinsurance program with no risk adjustment. This mimics the existing reinsurance system in place in 2014 in the ACA Health Insurance Marketplace, the same base case as used in LEM (2015). We do not examine payment systems that combine risk adjustment and reinsurance.

[5] Following FGM, EM, EJK, and LEM 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.

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 include 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 required 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 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.

In order to calculate empirical selection incentives, we predict 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. Starting from the same categories used in EJK, we used a physician consultant (in internal medicine) to help narrow down the analysis to 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. The key spending variable we focus on is the covered charge, a financial variable on claims that best approximates the medical resources used in treating patients.

We examine four different forms of risk adjustment. The first 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 for the US for Medicare payments to managed care plans and the ACA Health Insurance Marketplace risk adjustment. Finally, we examine one reinsurance program calibrated to approximate the 2014 reinsurance program in the Health Insurance Marketplace, namely one in which 80 percent of costs above an attachment point of $60,000 per year is covered by a government reinsurance program. We implicitly adjust the premiums paid to reflect the payout of this reinsurance, without adding any administrative costs, and examine it in the absence of any risk adjustment program.

IV. Estimation Strategy

To obtain the EM selection 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, which we take from EMZ, and the standard deviation of individual level profits, which we calculate from our data. Finally, we need an estimate of ϕ which we discuss below.

Some readers may be concerned that we focus on linear predictive model specifications. Although various advanced econometric methods, including generalized linear model specifications and two-part models using linear and transformed expenditures have been developed to overcome the classical problems of large proportion of zero expenditures and long right trail of health expenditures, several recent studies (EM, 2007, and Dusheiko et. al., 2009) have shown that with very large samples, ordinary least squares model (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 the rest of our analysis, 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 subsequent year spending. 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 found the most predictive information set to use to predict spending by type of services was disaggregated spending by type of service the preceding year. Specifically, we estimate a model of the following form.

$$m_{s,t} = f(agegender, m_{1,t-1}, ..., m_{33,t-1}) .$$

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 (or at least this version of the 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, arbitrarily, that consumers are only half as responsive to expected spending changes as premiums, suggesting that the elasticity of plan choice to 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 1.63×10^{-5} as our point estimate for ϕ, which is to say that increasing expected spending on medical care by \$1000 increases the market share of a plan by 0.0163, 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? How does the actual selection evolve over time? To do this, we follow the methodology of EJK (2013) and both test the associations statistically and examine patterns graphically. We do this by comparing changes over time, across plan type, and across specific plans. For this analysis we create a variable that we call MEANRATIO. The MEANRATIO for each group of interest and each service is calculated as the percent of total plan spending on a given service in a given group of interest divided by 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 mean 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. The reasons for this normalization in our mean ratio are twofold. The first one is that some expensive services have small means due to extremely low frequency. Without normalization, services with large means affect profits more in dollar terms, but perhaps less as a proportion of their mean. The second reason is that this normalization removes systematic price differences over time, by plan type, and across plans. For example, if PPOs negotiate discounts across all services relative to COMP and this is reflected in their premiums, then this does not affect selection incentives or our MEANRATIO variable.

V. Empirical Results

A. Descriptive Statistics

Table 1 provides summary statistics for our sample, showing means and standard deviations of total spending, concurrent and prospective risk scores, plan type market shares, age, gender, and profits. Although our data span seven plan types, we focus our analysis on five plan types of particular interest:, EPO, HMO, PPO, CDHP and HDHP.

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. The two parameters which are constant for the calculation in this table are the standard deviation of individual profits σ_π which is calculated as 58,196 for this payment system, and the insurance demand responsiveness parameter, which is $\phi = 1.638E - 05$ for our base case. The first column shows mean spending on each detailed service, while columns (2) through (4) show the demand elasticity η_s from EMZ, the predictability, and the predictiveness, respectively. The final two columns show two selection incentive measures. Column (5) uses the EM definition of its selection index, which is the product of only the predictiveness and predictability terms. Column (6) calculates the selection incentives using all five 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 (5) above. The elasticity on overall spending suggests that tightening the shadow price of all medical services by one percent will raise average profits by 1.39 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 visit[6], 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 full selection elasticity (FSE) for these services since the demand elasticities (shown in the first column) are implausible, and we therefore omit these four services from the rest of our main analysis. (Although results for these services are presented in the appendix).

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=1.59) as very prone to use for selection, with nonsurgical supplies/devices (FSE=1.25) and PET scans (FSE=1.00) also having high incentives for selection.[7] 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.

[6] 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.
[7] As in Brot-Goldberg (2015) the category "other" has an above average elasticity, and hence a larger FSE of 1.04.

Table 3 recalculates our full selection elasticity for five payment systems on 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 age-sex group. We see here that age sex adjustment has only a modest effect on incentives, lowering the average elasticity only from 0.67 to 0.63.

Column (3) implements prospective diagnosis-based (DX) risk adjustment using the prospective DxCG relative risk score (RRS), while column (4) presents the results using the DxCG 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 - 0.41/0.67) in average incentives to select, while concurrent risk adjustment achieves a 45 percent reduction in the weighted average.

The final column in Table 3 presents our full selection elasticity for a payment system with no risk adjustment, but with a reinsurance program that is chosen so as to mimic the program in place for the existing Marketplace, with 80 percent reinsurance coverage for the plan after spending $60,000 in total on an individual. As would be expected, the reinsurance program is highly effective at reducing the overall variability of profits. The final row shows that this reinsurance program 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 0.50, which is only a 25 percent reduction relative to the base case. In short, reinsurance is less successful at reducing selection incentives than either risk adjustment model.

The superiority of risk adjustment over reinsurance in our results is a surprise. 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 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.[8] We did not do any estimation of payment systems that combine risk adjustment with reinsurance, although this will no doubt reduce selection incentives even more.

[8] 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.

Figure 1 summarizes the selection effects for each type of service. Here the patterns across services, and across different forms of reinsurance are visible, as well as the modest superiority of concurrent risk adjustment over prospective, and the weaker performance of 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. 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. Incentives for single versus family coverage can be reflected in difference in their deductibles and stoplosses, while differences in incentives across risk scores may be informative about how risk adjustment affects incentives. Although we do not observe premiums charged to enrollees, they remain one of the most important selection tools that influence plan choices.

Table 4a-4c presents separate selection elasticities for five different partitions of our data: by plan types, by year, by single versus family plan coverage, by age groups, and by prospective relative risk scores (RRS). In each case we used the same model of expectations for each subsample, but recalculated three of the five components of the selection elasticities for each population subgroup separately. Hence the predictability, predictiveness and profit variation all vary by subgroup, while the demand elasticity and insurance responsiveness parameter (ϕ) were held constant. Confirming the results in EJK (2013) we find that the selection measures are highly stable across subsets of the total population with most correlations above .94. To simplify the presentation, we show in Table 4 the incentives only for the no risk adjustment case.

Table 4a calculates our FSE by seven different plan types. (Recall from Table 1 that even our least common plan type (EPO) still has information on 94,385 people). Here, as in Ellis and Zhu (forthcoming), we have ordered plan types in the order of plan types that emphasize supply side incentives the most to those that rely on demand side incentives to control costs. Two patterns are dominant. First, there is a very high correlation between the FSE across plan types: across all service categories shown the correlations range from 0.948 (comprehensive plans) to 0.998 (PPOs). Second, on average the full selection elasticities are modestly lower for plan types that rely on supply side incentives such as EPOs and HMOs than those that rely on demand side incentives, such as CDHP and HDHP. Although varying, selection incentives are present across all plan types.

Table 4b examines whether selection incentives vary over time and between single and family contracts. For the time analysis we divided the sample into three intervals spanning our sample period of 2007 to 2014, and deflated the elasticities and profit variation by the personal consumption expenditure deflator for health care, so the changes shown reflect the inflation-adjusted changes in incentives. Our results show evidence of a meaningful upward trend in selection incentives, largely driven by increases in the standard deviation of profitability, not in the underlying correlations. Because we were interested in whether this result also holds for payment systems with risk adjustment and reinsurance, figure 4 plots the changes in the weighted average FSE over our three time periods for all five of our payment systems. Our FSE is increasing in all five sets of calculations, although selection incentives grow more slowly in the reinsurance program than the rest. This last pattern likely reflects that we used a fixed insurance threshold of $60,000 which will have become modestly more binding over our sample period as covered costs (and their variability) increase over time.

Table 4b also shows selection indices for single versus family coverage enrollees, and demonstrates no meaningful differences at the individual level. This is relevant since both the EM (2007) and the EJK (2013) focus entirely on individual level selection incentives. Our results show that if one focuses on individual level selection incentives, then there is essentially no difference in incentives between the two sets of enrollees. The important caveat to this is that family contracts by their nature imply sets of individuals, with correlated spending patterns, make the same plan choice. We did not separately model family level selection incentives, which would entail pooling multiple individuals and perhaps looking at both service level and total profits at the household rather than individual level.

Table 4c presents the results from calculating the FSE by four age groups and by four intervals of prospective relative risk scores. The results by age group are surprising in that they suggest greater full selection elasticities from distorting services for children than for adults. Using expenditure weighted averages, the incentives for selection are highest among children aged 6 to 20 and lowest among young adults aged 21 to 45. Note that implicit in these calculations is the idea that premiums also vary by these four age groups, so it is variability in profits within each group that are driving the results. 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=0.681, which is the lowest correlation of any subgroup evaluated.

The results in Table 4c by intervals of prospective relative risk scores (RRS) are also interesting. Note that we did not use any risk adjustment in these calculations, so they reflect the incentive to select among people with low, medium high and very high expected costs. It is no surprise that incentives to select grow enormously across risk scores, with FSE that are more than five times higher on average for very high RRS categories. The final row shows that the calculated risk scores remain moderately correlated for lower RRS individuals

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 2 and 3 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 full sample[9]. The vertical axis measures the MEANRATIO defined in section IV, namely the ratio of spending share of a service for a subgroup to the overall sample average spending share. By construction, the weighted average of MEANRATIO for each type of service is one. We have omitted the Comprehensive and POS plan types from the two figures to simplify the figure. Figure 2 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. HDHP and CDHP are similar to 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

[9] We could use the selection elasticities generated specifically for each subgroup, but choose instead to hold the FSE constant across subgroups due to concerns about spurious correlations between the measures on the two axes if we allow the selection elasticities to also vary.

the plan. Figure 3 replicates that analysis for the payment system with concurrent risk adjustment. The selection elasticities are lower, but the same pattern emerges, suggesting that risk adjustment does not entirely remove the incentives for selection.

E. *Sensitivity analysis to alternative values of phi.*

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 is to say 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 which surprised us is that we find evidence that risk adjustment is more effective at reducing selection incentives than 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. We have not explored how combinations of risk adjustment and risk selection change this finding.

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 combinations of risk adjustment and reinsurance are destined to do even better. 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 (FSE) Results
(after removing four insigificant/wrong sign services)

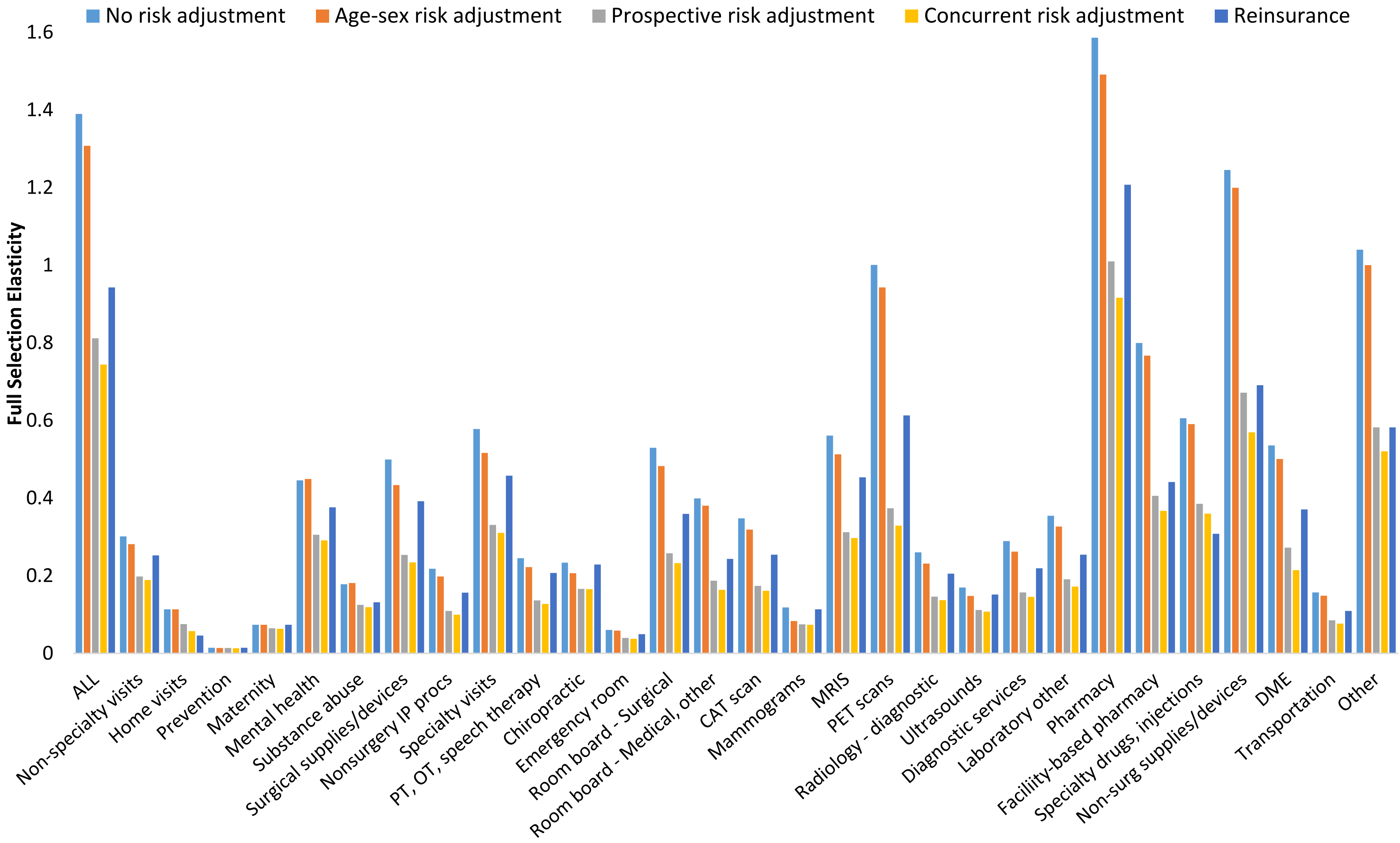

Figure 2 – For each of 29 types of service, plot of share of spending relative to overall share of spending versus full selection elasticities, by five plan types with no risk adjustment (four insignificant services omitted)

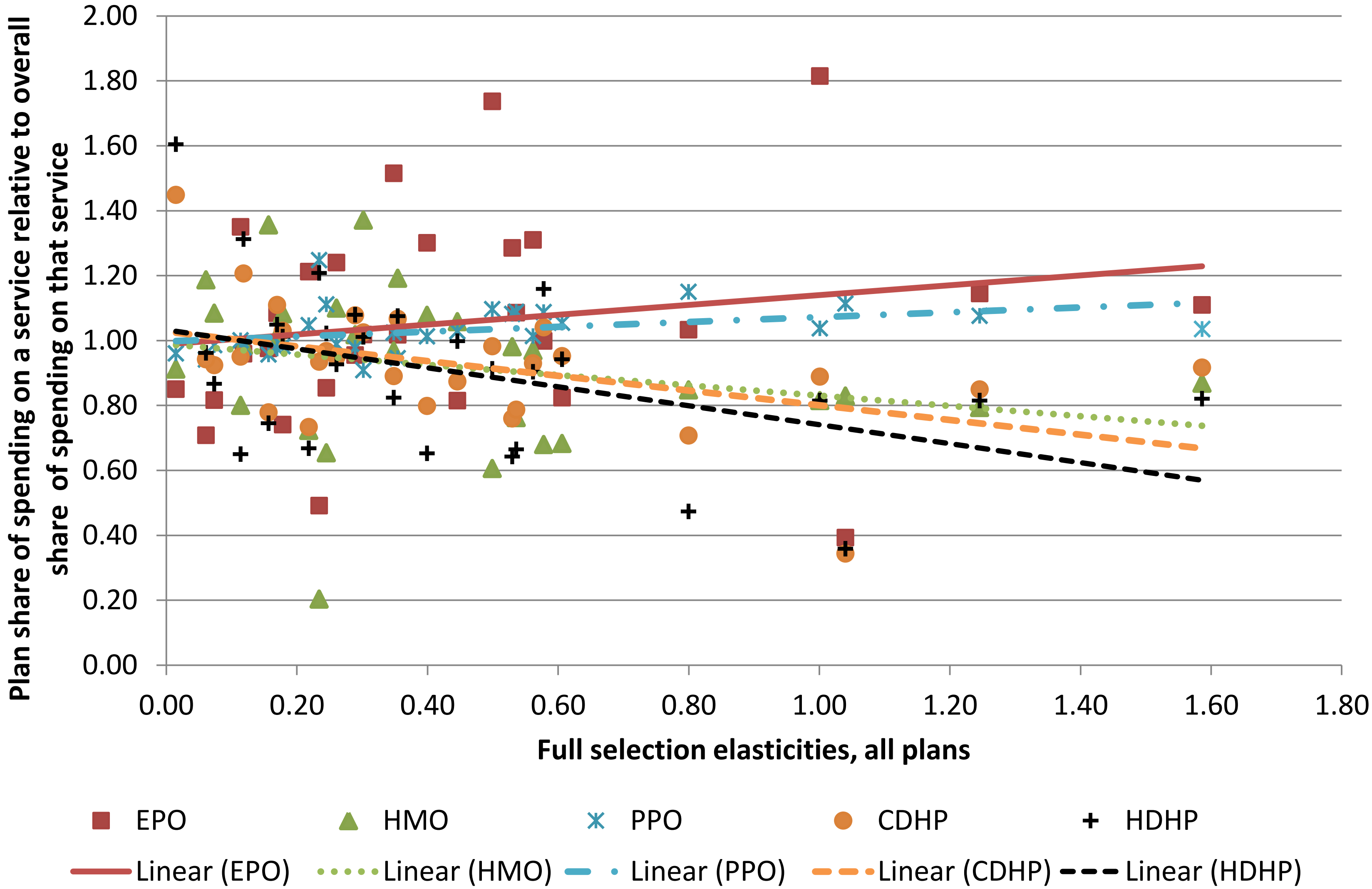

Figure 3 – For each of 29 types of service, plot of share of spending relative to overall share of spending versus full selection elasticities, by five plan types with concurrent risk adjustment (four insignificant services omitted)

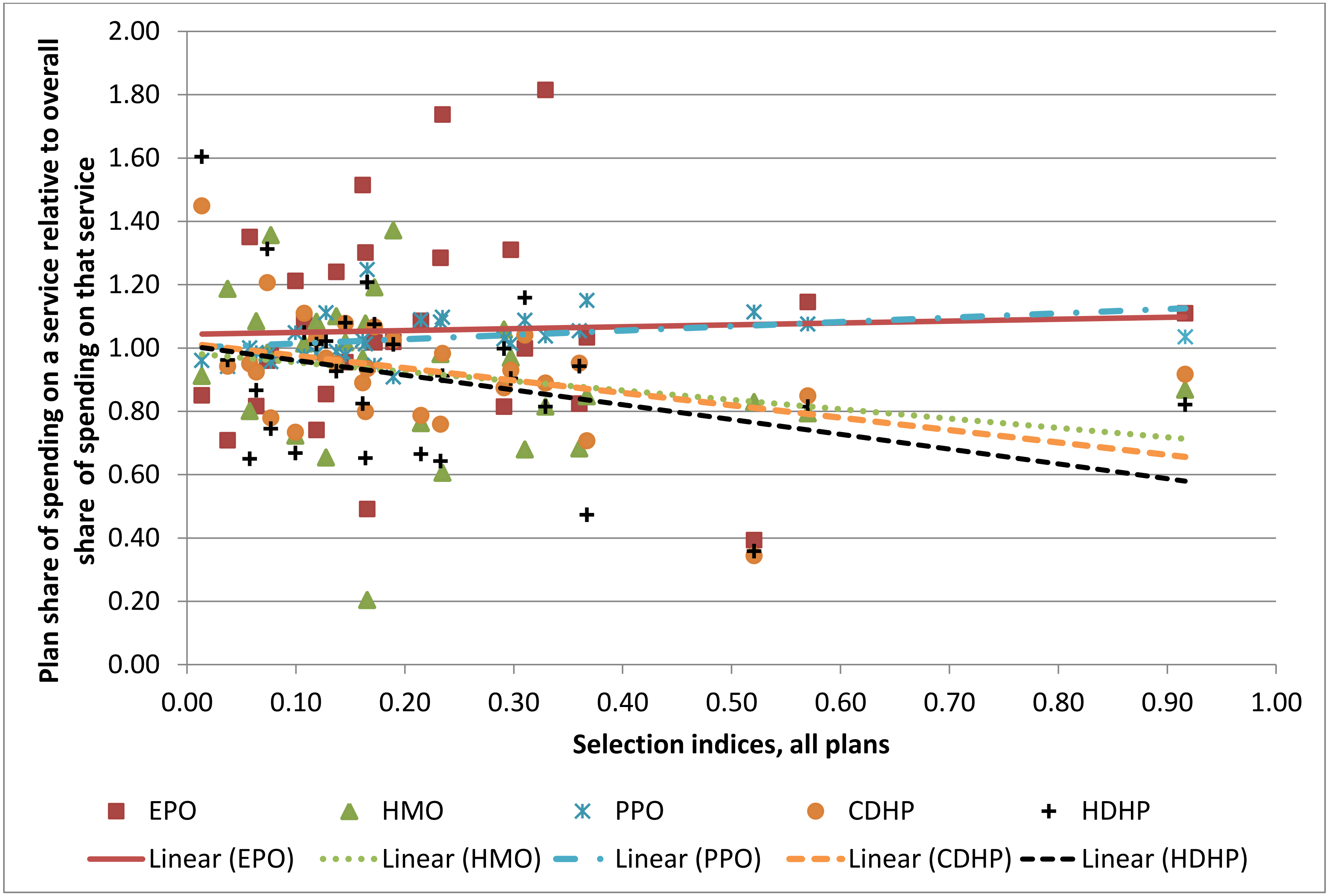

Figure 4 – Evolution of weighted average of full selection elasticities for 29 services over time (deflated)

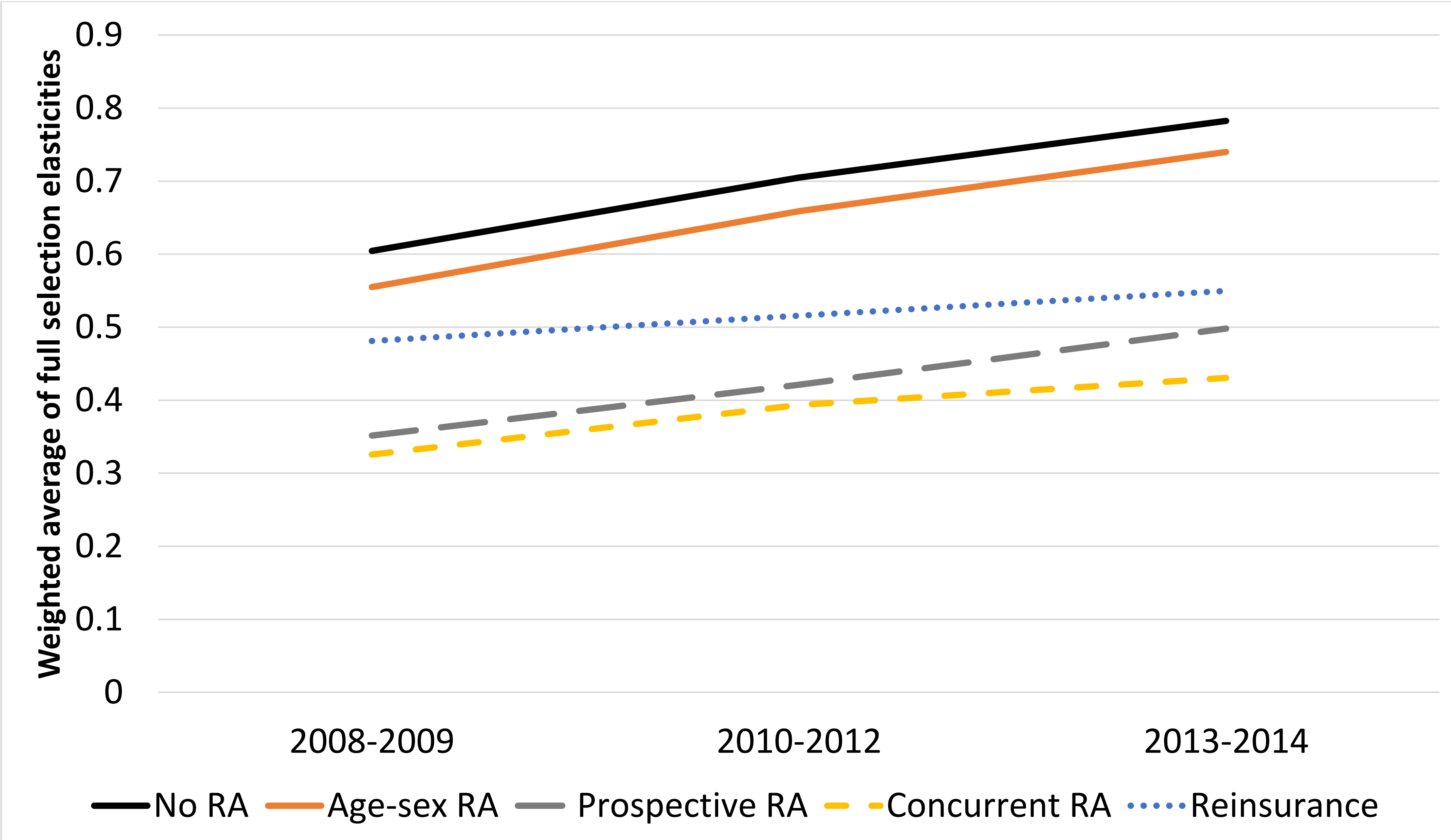

Table 1---Basic statistics by plan types

	N	Age		Current year total spending		Prior year total spending	
		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
By Plan type:							
EPO	94,385	35.3	18.6	4,469	14,619	3,888	11,841
HMO	2,486,259	30.7	17.7	2,757	13,792	2,507	12,295
POS	1,491,322	34.1	17.8	4,233	15,641	3,823	13,154
PPO	8,305,156	35.0	18.5	4,869	17,724	4,407	14,937
Comprehensive	216,391	42.2	18.8	6,300	21,080	5,775	18,343
CDHP	1,162,945	32.9	17.9	4,018	16,594	3,615	13,588
HDHP	240,861	32.5	18.1	3,693	15,445	3,348	12,787

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.

Table 2---Selection incentive components for 33 types of service with No Risk Adjustment

		MEAN	Elasticity	CV	$\rho_{\hat{m}_s,\pi}$	EM Selection index	Full Selection Elasticity
	All types of spending	$4,354.56	-0.327	6.75	-0.50	3.41	1.39
	By TOS:						
1	Non-specialty visits	293.13	-0.156	3.24	-0.30	0.98	0.30
2	Home visits	11.54	-0.004	273.28	-0.11	29.87	0.11
3	Prevention	50.37	-0.014	2.48	-0.03	0.08	0.01
4	Maternity	133.61	-0.063	8.80	-0.02	0.18	0.07
5	Mental health	103.62	-0.180	16.31	-0.09	1.54	0.45
6	Substance abuse	20.32	-0.052	59.59	-0.04	2.56	0.18
7	Major surgical procedures	86.49	0.057	7.11	-0.36	2.59	-0.20
8	Surgical supplies/devices	56.61	-0.167	6.73	-0.31	2.08	0.50
9	Nonsurgery IP procs	85.50	-0.059	8.84	-0.32	2.80	0.22
10	Specialty visits	708.50	-0.224	4.75	-0.35	1.66	0.58
11	Dialysis	30.27	0.015	205.75	-0.19	39.28	-0.56
12	PT, OT, speech therapy	98.61	-0.102	8.58	-0.17	1.47	0.25
13	Chiropractic	25.66	-0.147	12.80	-0.05	0.62	0.23
14	Hospice	0.53	3.919	218.09	-0.05	11.06	-45.21
15	Emergency room	219.51	-0.029	4.65	-0.25	1.14	0.06
16	Room board - Surgical	233.59	-0.128	8.89	-0.37	3.29	0.53
17	Room board - Medical, other	141.86	-0.067	16.41	-0.32	5.24	0.40
18	CAT scan	62.76	-0.104	8.24	-0.30	2.46	0.35
19	Mammograms	31.31	-0.072	6.80	-0.10	0.67	0.12
20	MRIS	73.77	-0.210	6.13	-0.29	1.75	0.56
21	PET scans	6.54	-0.130	44.30	-0.16	7.01	1.00
22	Radiology - diagnostic	71.72	-0.101	4.29	-0.39	1.66	0.26
23	Radiology - therapeutic	36.69	0.049	13.99	-0.26	3.57	-0.22
24	Ultrasounds	32.27	-0.095	4.24	-0.20	0.83	0.17
25	Diagnostic services	116.92	-0.099	5.32	-0.38	2.00	0.29
26	Laboratory other	183.15	-0.109	8.05	-0.30	2.37	0.35
27	Pharmacy	959.51	-0.328	12.00	-0.34	4.02	1.59
28	Facility-based pharmacy	153.20	-0.102	24.01	-0.30	7.20	0.80
29	Specialty drugs, injections	136.74	-0.045	51.83	-0.25	12.99	0.61
30	Non-surg supplies/devices	61.29	-0.179	36.69	-0.17	6.26	1.25
31	DME	27.36	-0.122	15.88	-0.22	3.55	0.54
32	Transportation	23.95	-0.047	8.13	-0.30	2.46	0.16
33	Other	83.79	-0.147	38.03	-0.17	6.38	1.04
	ϕ = derivative of profit with respect to expected spending						1.638E-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 one reinsurance model

	TOS	No risk adjustment	Age-sex risk adjustment	Prospective Dx risk adjustment	Concurrent Dx risk adjustment	Reinsurance: 80% after $60,000
	All types of spending	1.39	1.31	0.81	0.74	0.94
	By TOS:					
1	Non-specialty visits	0.30	0.28	0.20	0.19	0.25
2	Home visits	0.11	0.11	0.08	0.06	0.05
3	Prevention	0.01	0.01	0.01	0.01	0.01
4	Maternity	0.07	0.07	0.06	0.06	0.07
5	Mental health	0.45	0.45	0.31	0.29	0.38
6	Substance abuse	0.18	0.18	0.13	0.12	0.13
8	Surgical supplies/devices	0.50	0.43	0.25	0.23	0.39
9	Nonsurgery IP procs	0.22	0.20	0.11	0.10	0.16
10	Specialty visits	0.58	0.52	0.33	0.31	0.46
12	PT, OT, speech therapy	0.25	0.22	0.14	0.13	0.21
13	Chiropractic	0.23	0.21	0.17	0.17	0.23
15	Emergency room	0.06	0.06	0.04	0.04	0.05
16	Room board - Surgical	0.53	0.48	0.26	0.23	0.36
17	Room board - Medical, other	0.40	0.38	0.19	0.16	0.24
18	CAT scan	0.35	0.32	0.17	0.16	0.25
19	Mammograms	0.12	0.08	0.07	0.07	0.11
20	MRIS	0.56	0.51	0.31	0.30	0.45
21	PET scans	1.00	0.94	0.37	0.33	0.61
22	Radiology - diagnostic	0.26	0.23	0.15	0.14	0.21
24	Ultrasounds	0.17	0.15	0.11	0.11	0.15
25	Diagnostic services	0.29	0.26	0.16	0.15	0.22
26	Laboratory other	0.35	0.33	0.19	0.17	0.25
27	Pharmacy	1.59	1.49	1.01	0.92	1.21
28	Facility-based pharmacy	0.80	0.77	0.41	0.37	0.44
29	Specialty drugs, injections	0.61	0.59	0.39	0.36	0.31
30	Non-surg supplies/devices	1.25	1.20	0.67	0.57	0.69
31	DME	0.54	0.50	0.27	0.21	0.37
32	Transportation	0.16	0.15	0.09	0.08	0.11
33	Other	1.04	1.00	0.58	0.52	0.58
	Mean weighted selection elasticity	0.67	0.63	0.41	0.37	0.50
	ϕ = derivative of the probability of choosing a plan with respect to expected spending	1.638E-05	1.638E-05	1.638E-05	1.638E-05	1.638E-05
	σ_π = Standard deviation of individual profit	58,196	57,621	52,898	40,852	32,291
	Correlation with base case	1	0.999	0.974	0.966	0.968

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 4a---Comparison of full selection elasticities across subgroups: by plan type

		Plan type						
	TOS	EPO	HMO	POS	PPO	Comp	CDHP	HDHP
	ALL	1.15	1.11	1.22	1.43	1.79	1.61	1.40
1	Non-specialty visits	0.28	0.30	0.30	0.30	0.46	0.30	0.26
2	Home visits	0.07	0.09	0.13	0.09	0.30	0.17	0.07
3	Prevention	0.01	0.02	0.01	0.01	0.01	0.01	0.01
4	Maternity	0.07	0.08	0.07	0.07	0.06	0.08	0.08
5	Mental health	0.33	0.37	0.45	0.44	0.48	0.50	0.53
6	Substance abuse	0.12	0.10	0.19	0.17	0.12	0.23	0.59
8	Surgical supplies/devices	0.52	0.44	0.49	0.50	0.53	0.52	0.54
9	Nonsurgery IP procs	0.29	0.20	0.23	0.21	0.29	0.24	0.22
10	Specialty visits	0.58	0.52	0.63	0.58	0.70	0.54	0.52
12	PT, OT, speech therapy	0.23	0.23	0.24	0.24	0.31	0.26	0.22
13	Chiropractic	0.21	0.26	0.22	0.22	0.26	0.23	0.22
15	Emergency room	0.06	0.05	0.06	0.06	0.08	0.07	0.06
16	Room board - Surgical	0.41	0.41	0.51	0.56	0.48	0.54	0.53
17	Room board - Medical, other	0.34	0.35	0.36	0.42	0.54	0.39	0.31
18	CAT scan	0.29	0.28	0.34	0.35	0.40	0.39	0.48
19	Mammograms	0.12	0.12	0.11	0.12	0.12	0.12	0.11
20	MRIS	0.50	0.49	0.52	0.57	0.67	0.58	0.64
21	PET scans	0.88	0.77	0.97	1.03	0.96	1.07	1.15
22	Radiology - diagnostic	0.27	0.24	0.25	0.26	0.34	0.27	0.28
24	Ultrasounds	0.17	0.16	0.16	0.17	0.19	0.18	0.18
25	Diagnostic services	0.28	0.27	0.28	0.29	0.29	0.32	0.32
26	Laboratory other	0.31	0.44	0.31	0.34	0.44	0.35	0.41
27	Pharmacy	1.22	1.27	1.25	1.66	1.64	1.59	1.89
28	Facility-based pharmacy	0.45	0.62	0.91	0.77	1.26	1.10	1.23
29	Specialty drugs, injections	0.47	0.55	0.41	0.61	0.54	1.04	0.45
30	Non-surg supplies/devices	0.78	1.18	0.88	1.42	1.50	1.11	1.28
31	DME	0.53	0.47	0.54	0.53	0.95	0.61	0.44
32	Transportation	0.12	0.11	0.13	0.17	0.29	0.18	0.11
33	Other	0.96	0.92	0.82	1.07	0.86	1.38	1.45
	Weighted average full selection elasticity	0.52	0.50	0.55	0.70	0.76	0.65	0.67
	σ_{π} = Standard deviation of individual profit	50641	47776	54182	61398	73024	57482	53502
	Correlation with base case	0.966	0.988	0.972	0.998	0.948	0.963	0.958

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

		Year groups			Single/family coverage	
	TOS	2008-2009	2010-2012	2013-2014	Single	Family
	ALL	1.28	1.47	1.69	1.35	1.40
1	Non-specialty visits	0.31	0.32	0.33	0.32	0.30
2	Home visits	0.08	0.12	0.14	0.06	0.13
3	Prevention	0.02	0.02	0.02	0.02	0.01
4	Maternity	0.08	0.08	0.08	0.06	0.08
5	Mental health	0.46	0.46	0.49	0.44	0.45
6	Substance abuse	0.13	0.13	0.27	0.14	0.19
8	Surgical supplies/devices	0.50	0.52	0.58	0.45	0.52
9	Nonsurgery IP procs	0.21	0.23	0.27	0.19	0.23
10	Specialty visits	0.56	0.61	0.64	0.60	0.57
12	PT, OT, speech therapy	0.25	0.25	0.29	0.24	0.24
13	Chiropractic	0.25	0.24	0.25	0.24	0.23
15	Emergency room	0.06	0.06	0.07	0.06	0.06
16	Room board - Surgical	0.56	0.54	0.63	0.49	0.55
17	Room board - Medical, other	0.44	0.40	0.47	0.35	0.42
18	CAT scan	0.32	0.37	0.46	0.35	0.35
19	Mammograms	0.13	0.12	0.12	0.11	0.12
20	MRIS	0.55	0.58	0.68	0.55	0.56
21	PET scans	0.92	1.05	1.25	0.91	1.03
22	Radiology - diagnostic	0.26	0.27	0.32	0.26	0.26
24	Ultrasounds	0.18	0.18	0.19	0.17	0.17
25	Diagnostic services	0.28	0.30	0.35	0.27	0.29
26	Laboratory other	0.32	0.37	0.45	0.33	0.36
27	Pharmacy	1.31	1.74	1.96	1.44	1.63
28	Facility-based pharmacy	0.67	0.87	1.15	0.77	0.81
29	Specialty drugs, injections	0.67	0.68	0.57	0.48	0.66
30	Non-surg supplies/devices	0.93	1.39	2.01	1.45	1.19
31	DME	0.56	0.57	0.58	0.43	0.57
32	Transportation	0.15	0.15	0.21	0.15	0.16
33	Other	0.73	1.18	2.31	1.06	1.04
	Weighted average full selection elasticity	0.60	0.70	0.78	0.64	0.66
	Profit SD	54199	61678	68296	64250	56509
	Correlation with base case	0.9805	0.9988	0.9451	0.987	0.999

Table 4c---Comparison of full selection elasticities across subgroups: age and RRS groups

		Age groups				Prospective RRS intervals			
	TOS	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	1.70	1.65	1.19	1.33	0.40	0.44	0.59	2.81
1	Non-specialty visits	0.25	0.24	0.27	0.33	0.17	0.17	0.19	0.58
2	Home visits	0.21	0.23	0.10	0.05	0.01	0.02	0.02	0.14
3	Prevention	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01
4	Maternity	0.16	0.08	0.09	0.07	0.07	0.06	0.05	-0.06
5	Mental health	0.91	0.44	0.45	0.44	0.24	0.28	0.33	0.55
6	Substance abuse	0.57	0.20	0.19	0.15	0.07	0.11	0.19	0.19
8	Surgical supplies/devices	1.33	0.44	0.43	0.45	0.19	0.19	0.21	0.48
9	Nonsurgery IP procs	0.43	0.32	0.20	0.19	0.07	0.07	0.08	0.31
10	Specialty visits	0.63	0.45	0.49	0.55	0.25	0.25	0.29	0.97
12	PT, OT, speech therapy	0.51	0.25	0.19	0.23	0.12	0.12	0.13	0.29
13	Chiropractic	0.18	0.20	0.21	0.21	0.18	0.17	0.17	0.04
15	Emergency room	0.04	0.05	0.06	0.07	0.03	0.03	0.04	0.13
16	Room board - Surgical	1.43	0.80	0.49	0.45	0.14	0.14	0.16	0.79
17	Room board - Medical, other	0.45	0.64	0.36	0.35	0.07	0.08	0.10	0.60
18	CAT scan	0.37	0.22	0.28	0.37	0.11	0.12	0.14	0.56
19	Mammograms	0.07	0.10	0.10	0.09	0.09	0.08	0.07	0.05
20	MRIS	1.07	0.48	0.47	0.55	0.24	0.23	0.28	0.76
21	PET scans	1.28	1.14	1.00	0.94	0.15	0.16	0.24	1.15
22	Radiology - diagnostic	0.31	0.22	0.22	0.25	0.11	0.11	0.12	0.39
24	Ultrasounds	0.23	0.17	0.15	0.16	0.11	0.10	0.11	0.20
25	Diagnostic services	0.41	0.31	0.25	0.26	0.11	0.11	0.12	0.44
26	Laboratory other	0.44	0.51	0.27	0.34	0.12	0.12	0.15	0.77
27	Pharmacy	1.37	2.64	1.41	1.36	0.54	0.62	0.81	2.43
28	Facility-based pharmacy	0.73	0.76	0.84	0.77	0.11	0.13	0.21	1.28
29	Specialty drugs, injections	0.70	1.53	0.63	0.48	0.06	0.13	0.31	0.82
30	Non-surg supplies/devices	2.11	1.06	0.87	1.48	0.20	0.22	0.26	2.33
31	DME	2.10	0.97	0.41	0.43	0.14	0.15	0.17	0.72
32	Transportation	0.61	0.10	0.13	0.16	0.05	0.05	0.06	0.34
33	Other	4.46	1.23	0.98	0.82	0.20	0.19	0.33	2.18
	Weighted average full selection elasticity	0.66	0.87	0.54	0.63	0.21	0.26	0.33	1.12
	Profit SD	49067	42173	48425	74861	28737	48189	72357	219521
	Correlation with base case	0.681	0.898	0.982	0.977	0.760	0.784	0.840	0.960

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 selection elasticity for			Concurrent risk adjustment selection elasticity for		
	TOS	0.5 ϕ	ϕ	2 ϕ	0.5 ϕ	ϕ	2 ϕ
	ALL	0.86	1.39	2.45	0.54	0.74	1.16
1	Non-specialty visits	0.23	0.30	0.45	0.17	0.19	0.22
2	Home visits	0.06	0.11	0.22	0.03	0.06	0.11
3	Prevention	0.01	0.01	0.02	0.01	0.01	0.01
4	Maternity	0.07	0.07	0.08	0.06	0.06	0.06
5	Mental health	0.31	0.45	0.71	0.24	0.29	0.40
6	Substance abuse	0.12	0.18	0.31	0.09	0.12	0.19
8	Surgical supplies/devices	0.33	0.50	0.83	0.20	0.23	0.30
9	Nonsurgery IP procs	0.14	0.22	0.38	0.08	0.10	0.14
10	Specialty visits	0.40	0.58	0.93	0.27	0.31	0.40
12	PT, OT, speech therapy	0.17	0.25	0.39	0.11	0.13	0.15
13	Chiropractic	0.19	0.23	0.32	0.16	0.17	0.18
15	Emergency room	0.05	0.06	0.09	0.03	0.04	0.05
16	Room board - Surgical	0.33	0.53	0.93	0.18	0.23	0.34
17	Room board - Medical, other	0.23	0.40	0.73	0.12	0.16	0.26
18	CAT scan	0.23	0.35	0.59	0.13	0.16	0.22
19	Mammograms	0.10	0.12	0.16	0.07	0.07	0.08
20	MRIS	0.39	0.56	0.91	0.25	0.30	0.38
21	PET scans	0.57	1.00	1.87	0.23	0.33	0.53
22	Radiology - diagnostic	0.18	0.26	0.42	0.12	0.14	0.17
24	Ultrasounds	0.13	0.17	0.25	0.10	0.11	0.12
25	Diagnostic services	0.19	0.29	0.48	0.12	0.15	0.19
26	Laboratory other	0.23	0.35	0.60	0.14	0.17	0.24
27	Pharmacy	0.96	1.59	2.84	0.62	0.92	1.50
28	Faciliity-based pharmacy	0.45	0.80	1.50	0.23	0.37	0.63
29	Specialty drugs, injections	0.33	0.61	1.17	0.20	0.36	0.68
30	Non-surg supplies/devices	0.71	1.25	2.31	0.37	0.57	0.96
31	DME	0.33	0.54	0.95	0.17	0.21	0.31
32	Transportation	0.10	0.16	0.27	0.06	0.08	0.11
33	Other	0.59	1.04	1.93	0.33	0.52	0.89
	Weighted average full selection elasticity	0.41	0.66	1.15	0.27	0.36	0.56
	ϕ	8E-06	1.6E-05	3.3E-05	8.2E-06	1.6E-05	3.3E-05
	Profit SD	58196	58195.5	58195.5	40851.7	40851.7	40851.7
	Correlation with base case	0.994	1.000	0.984	0.983	1.000	0.950

APPENDIX A

In this appendix, we formally derive our full selection elasticity formula, which closely follows the derivations in Ellis and McGuire (2007) and Ellis, Jiang and Kuo (2013).

Let $\hat{m}_{is}$ denote the amount that individual i expects the plan will spend on providing service s and let $\hat{m}_i = \{\hat{m}_{i1}, \hat{m}_{i2}, ..., \hat{m}_{iS}\}$. The utility to individual i from a plan is $u_i(\hat{m}_i) = v_i(\hat{m}_i) + \mu_i$, where μ_i is a random term with distribution function Φ_i. Utility is assumed to be additively separable in expected spending on each service, and hence it can be written as $v_i(\hat{m}_i) = \sum_s v_{is}(\hat{m}_{is})$ which implies that all cross price effects are zero.

Individual i chooses this plan if $\mu_i > \bar{\mu}_i - v_i(\hat{m}_i)$, where $\bar{\mu}_i$ is the valuation the individual places on the next best alternative plan. Let q_s denote the service-specific shadow price a plan sets to efficiently ration service s. The efficient quantity of services, $\hat{m}_i$, for the patient will satisfy $v_{is}^{'}(\hat{m}_i) = q_s$.

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

$$\pi(q) = \sum_i n_i(\hat{m}_i(q)) \left[r_i - \sum_s m_{is}(q_s) \right], \tag{1}$$

where r_i is the revenue the plan receives for each individual and $n_i(\hat{m}_i) = 1 - \Phi_i(\bar{\mu}_i - v_i(\hat{m}_i))$ is the probability that health plan expects individual i would choose the plan. All individuals are assumed to share the same elasticity of demand for any service but elasticities can differ across services. Also the demand curve for insurance is assumed to be locally linear, or equivalently the enrollment function is assumed to be locally uniform for all i, so that $\Phi_i' = \phi$. [10]

The derivative of profit with respect to q_s is

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

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

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

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

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

Plug in $\Phi_i' = \phi$ and $v_{is}' = q_s$, then we have,

$$= \sum_i\{\phi q_s \widehat{m}_{is}' \pi_i - n_i m_{is}'\}$$

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

Assume that $\frac{q_s \widehat{m}_{is}'}{\widehat{m}_{is}} = \frac{q_s m_{is}'}{m_{is}} \equiv \eta_s$, then the above can be rewritten as,

$$= \sum_i\{\phi \eta_s \widehat{m}_{is}\pi_i - n_i \eta_s \frac{m_{is}}{q_s}\}$$

$$= \frac{\eta_s}{q_s}\{q_s \phi \sum_i \widehat{m}_{is}\pi_i - \sum_i n_i m_{is}\}$$

Denote $\overline{m}_s$ as the average spending on service s, and N as the total number of people in the plan, then we have, $N\overline{m}_s = \sum_i n_i m_{is}$. Also if we assume that plans have rationed services optimally, then at the first best $q_s = 1$. Taken together, we have,

$$\frac{\partial \pi(q)}{\partial q_s} = \eta_s(\phi \sum_i \widehat{m}_{is}\pi_i - N\overline{m}_s) \tag{2}$$

[10] Our hope is to relax this assumption in future empirical work, but this is the assumption used in FGM, EM, EJK, and LEM, which we continue here.

The EM full selection elasticity 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:

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

$$= \eta_s(\phi \sum_i \frac{\hat{m}_{is}\pi_i}{N\bar{m}_s} - 1) \tag{3}$$

To convert the expression to a correlation and a standard deviation, define the correlation coefficient $\rho_{\hat{m}_s,\pi} = \frac{\sum_i \hat{m}_{is}\pi_i - N\bar{m}_s\bar{\pi}}{N\sigma_{\hat{m}_s}\sigma_\pi}$ where $\bar{m}_s = \frac{\sum_i n_i \hat{m}_{is}}{N}$ and $\bar{\pi} = \frac{\sum_i n_i \pi_i}{N}$. We can then rewrite the full selection elasticity as:

$$FSE_s = \eta_s(\frac{N\sigma_{\hat{m}_s}\sigma_\pi}{\sum_i \hat{m}_{is}\pi_i - N\bar{m}_s\bar{\pi}}\rho_{\hat{m}_s,\pi}\phi \frac{\sum_i \hat{m}_{is}\pi_i}{N\bar{m}_s} - 1)$$

$$= \eta_s(\frac{\sigma_{\hat{m}_s}\sigma_\pi}{\sum_i \hat{m}_{is}\pi_i - N\bar{m}_s\bar{\pi}}\rho_{\hat{m}_s,\pi}\phi \frac{\sum_i \hat{m}_{is}\pi_i - N\bar{m}_s\bar{\pi} + N\bar{m}_s\bar{\pi}}{\bar{m}_s} - 1)$$

$$= \eta_s(\rho_{\hat{m}_s,\pi}\phi \frac{\sigma_{\hat{m}_s}\sigma_\pi}{\bar{m}_s} + \phi\bar{\pi} - 1) \tag{4}$$

If we assume that competition among many plans, while not eliminating the incentive to distort services, does drive profits down to zero, then $\bar{\pi} = 0$, and the FSE_s can be written as:

$$FSE_s = \eta_s(\sigma_\pi \phi \frac{\sigma_{\hat{m}_s}}{\bar{m}_s}\rho_{\hat{m}_s,\pi} - 1) \tag{5}$$

■

TABLE A-1 – DETAILED RESULTS OF SELECTION INCENTIVE COMPONENTS BY TYPE OF SERVICE WITH NO RISK ADJUSTMENT

	TOS	Elasticity	MEAN	STD	R^2	C.V.	No risk adjustment		
							$\rho_{\hat{m}_s,\pi}$	EM index	Selection Elasticity
	ALL	-0.33	4,354.56	29,375	0.25	6.75	-0.50	3.41	1.39
1	Non-specialty visits	-0.16	293.13	950	0.10	3.24	-0.30	0.98	0.30
2	Home visits	0.00	11.54	3,153	0.69	273.28	-0.11	29.87	0.11
3	Prevention	-0.01	50.37	125	0.21	2.48	-0.03	0.08	0.01
4	Maternity	-0.06	133.61	1,175	0.04	8.80	-0.02	0.18	0.07
5	Mental health	-0.18	103.62	1,691	0.13	16.31	-0.09	1.54	0.45
6	Substance abuse	-0.05	20.32	1,211	0.12	59.59	-0.04	2.56	0.18
7	Surgical procedures	0.06	86.49	615	0.01	7.11	-0.36	2.59	-0.20
8	Surgical supplies/devices	-0.17	56.61	381	0.01	6.73	-0.31	2.08	0.50
9	Nonsurgery IP procs	-0.06	85.50	756	0.03	8.84	-0.32	2.80	0.22
10	Specialty visits	-0.22	708.50	3,363	0.09	4.75	-0.35	1.66	0.58
11	Dialysis	0.01	30.27	6,228	0.49	205.75	-0.19	39.28	-0.56
12	PT, OT, speech therapy	-0.10	98.61	847	0.14	8.58	-0.17	1.47	0.25
13	Chiropractic	-0.15	25.66	329	0.41	12.80	-0.05	0.62	0.23
14	Hospice	3.92	0.53	116	0.09	218.09	-0.05	11.06	-45.21
15	Emergency room	-0.03	219.51	1,020	0.06	4.65	-0.25	1.14	0.06
16	Room board - Surgical	-0.13	233.59	2,076	0.01	8.89	-0.37	3.29	0.53
17	Room board - Medical, other	-0.07	141.86	2,328	0.04	16.41	-0.32	5.24	0.40
18	CAT scan	-0.10	62.76	517	0.07	8.24	-0.30	2.46	0.35
19	Mammograms	-0.07	31.31	213	0.28	6.80	-0.10	0.67	0.12
20	MRIS	-0.21	73.77	452	0.08	6.13	-0.29	1.75	0.56
21	PET scans	-0.13	6.54	290	0.17	44.30	-0.16	7.01	1.00
22	Radiology - diagnostic	-0.10	71.72	308	0.03	4.29	-0.39	1.66	0.26
23	Radiology - therapeutic	0.05	36.69	513	0.01	13.99	-0.26	3.57	-0.22
24	Ultrasounds	-0.09	32.27	137	0.04	4.24	-0.20	0.83	0.17
25	Diagnostic services	-0.10	116.92	622	0.03	5.32	-0.38	2.00	0.29
26	Laboratory other	-0.11	183.15	1,474	0.17	8.05	-0.30	2.37	0.35
27	Pharmacy	-0.33	959.51	11,514	0.61	12.00	-0.34	4.02	1.59
28	Faciliity-based pharmacy	-0.10	153.20	3,678	0.10	24.01	-0.30	7.20	0.80
29	Specialty drugs, injections	-0.05	136.74	7,087	0.34	51.83	-0.25	12.99	0.61
30	Non-surg supplies/devices	-0.18	61.29	2,249	0.25	36.69	-0.17	6.26	1.25
31	DME	-0.12	27.36	435	0.11	15.88	-0.22	3.55	0.54
32	Transportation	-0.05	23.95	195	0.01	8.13	-0.30	2.46	0.16
33	Other	-0.15	83.79	3,187	0.25	38.03	-0.17	6.38	1.04
	Weighted average full selection elasticity								0.66
	ϕ = derivative of profit with respect to expected spending								1.638E-05
	σ_π = Standard deviation of individual profit								58195.52

Table A-2 - DETAILED RESULTS OF SELECTION INCENTIVE COMPONENTS BY TYPE OF SERVICE WITH RISK ADJUSTMENT

	TOS	Age-sex risk adjustment			Prospective risk adjustment			Concurrent risk adjustment		
		$\rho_{\hat{m}_s,\pi}$	EM index	Selection Elasticity	$\rho_{\hat{m}_s,\pi}$	EM index	Selection Elasticity	$\rho_{\hat{m}_s,\pi}$	EM index	Selection Elasticity
	ALL	-0.47	3.17	1.31	-0.25	1.71	0.81	-0.28	1.90	0.74
1	Non-specialty visits	-0.26	0.85	0.28	-0.10	0.31	0.20	-0.10	0.32	0.19
2	Home visits	-0.11	30.05	0.11	-0.08	21.50	0.08	-0.08	20.79	0.06
3	Prevention	-0.01	0.04	0.01	0.00	0.01	0.01	0.00	0.01	0.01
4	Maternity	-0.02	0.18	0.07	0.00	0.03	0.06	0.00	0.01	0.06
5	Mental health	-0.10	1.58	0.45	-0.05	0.80	0.31	-0.06	0.92	0.29
6	Substance abuse	-0.04	2.64	0.18	-0.03	1.63	0.13	-0.03	1.93	0.12
7	Surgical procedures	-0.32	2.25	-0.18	-0.12	0.86	-0.10	-0.13	0.90	-0.09
8	Surgical supplies/devices	-0.25	1.69	0.43	-0.09	0.60	0.25	-0.09	0.60	0.23
9	Nonsurgery IP procs	-0.28	2.48	0.20	-0.11	0.98	0.11	-0.11	1.01	0.10
10	Specialty visits	-0.29	1.39	0.52	-0.12	0.56	0.33	-0.12	0.58	0.31
11	Dialysis	-0.19	39.27	-0.55	-0.12	23.77	-0.31	-0.14	29.50	-0.30
12	PT, OT, speech therapy	-0.15	1.25	0.22	-0.05	0.39	0.14	-0.04	0.38	0.13
13	Chiropractic	-0.03	0.43	0.21	-0.01	0.15	0.17	-0.01	0.18	0.17
14	Hospice	-0.05	10.68	-43.42	-0.02	4.21	-18.22	-0.02	4.56	-15.87
15	Emergency room	-0.23	1.08	0.06	-0.09	0.42	0.04	-0.09	0.43	0.04
16	Room board - Surgical	-0.33	2.93	0.48	-0.13	1.17	0.26	-0.14	1.22	0.23
17	Room board - Medical, other	-0.30	5.00	0.38	-0.13	2.10	0.19	-0.13	2.18	0.16
18	CAT scan	-0.27	2.19	0.32	-0.09	0.78	0.17	-0.10	0.82	0.16
19	Mammograms	-0.02	0.17	0.08	-0.01	0.04	0.07	-0.01	0.04	0.07
20	MRIS	-0.25	1.52	0.51	-0.09	0.56	0.31	-0.10	0.62	0.30
21	PET scans	-0.15	6.61	0.94	-0.05	2.16	0.37	-0.05	2.28	0.33
22	Radiology - diagnostic	-0.32	1.37	0.23	-0.12	0.52	0.15	-0.12	0.53	0.14
23	Radiology - therapeutic	-0.22	3.06	-0.19	-0.07	1.02	-0.09	-0.08	1.10	-0.08
24	Ultrasounds	-0.14	0.60	0.15	-0.05	0.21	0.11	-0.05	0.21	0.11
25	Diagnostic services	-0.33	1.74	0.26	-0.13	0.67	0.16	-0.13	0.69	0.15
26	Laboratory other	-0.26	2.13	0.33	-0.11	0.87	0.19	-0.11	0.88	0.17
27	Pharmacy	-0.31	3.76	1.49	-0.20	2.40	1.01	-0.22	2.68	0.92
28	Faciliity-based pharmacy	-0.29	6.93	0.77	-0.14	3.45	0.41	-0.16	3.90	0.37
29	Specialty drugs, injections	-0.25	12.77	0.59	-0.17	8.68	0.39	-0.20	10.40	0.36
30	Non-surg supplies/devices	-0.16	6.05	1.20	-0.09	3.18	0.67	-0.09	3.27	0.57
31	DME	-0.21	3.29	0.50	-0.09	1.42	0.27	-0.07	1.14	0.21
32	Transportation	-0.28	2.30	0.15	-0.12	0.95	0.09	-0.12	0.96	0.08
33	Other	-0.16	6.16	1.00	-0.09	3.43	0.58	-0.10	3.81	0.52
	Weighted average full selection elasticity			0.62			0.40			0.36
	ϕ = derivative of profit with respect to expected spending			1.638E-05			1.63756E-05			1.638E-05
	σ_π = Standard deviation of individual profit			57620.54			52897.95			40851.66

Table A-3 - DETAILED RESULTS OF SELECTION INCENTIVE COMPONENTS BY TYPE OF SERVICE WITH REINSURANCE

	TOS	Reinsurance		
		$\rho_{\hat{m}_s,\pi}$	EM index	Selection Elasticity
	ALL	-0.53	3.56	0.94
1	Non-specialty visits	-0.36	1.17	0.25
2	Home visits	-0.08	20.56	0.05
3	Prevention	-0.06	0.16	0.01
4	Maternity	-0.04	0.33	0.07
5	Mental health	-0.13	2.05	0.38
6	Substance abuse	-0.05	2.91	0.13
7	Surgical procedures	-0.40	2.86	-0.14
8	Surgical supplies/devices	-0.38	2.54	0.39
9	Nonsurgery IP procs	-0.35	3.09	0.16
10	Specialty visits	-0.42	1.98	0.46
11	Dialysis	-0.12	25.20	-0.21
12	PT, OT, speech therapy	-0.23	1.96	0.21
13	Chiropractic	-0.08	1.04	0.23
14	Hospice	-0.05	11.30	-27.34
15	Emergency room	-0.29	1.33	0.05
16	Room board - Surgical	-0.38	3.42	0.36
17	Room board - Medical, other	-0.31	5.02	0.24
18	CAT scan	-0.33	2.73	0.25
19	Mammograms	-0.16	1.09	0.11
20	MRIS	-0.36	2.19	0.45
21	PET scans	-0.16	7.01	0.61
22	Radiology - diagnostic	-0.45	1.95	0.21
23	Radiology - therapeutic	-0.28	3.94	-0.15
24	Ultrasounds	-0.27	1.14	0.15
25	Diagnostic services	-0.43	2.28	0.22
26	Laboratory other	-0.32	2.54	0.25
27	Pharmacy	-0.42	5.07	1.21
28	Faciliity-based pharmacy	-0.26	6.32	0.44
29	Specialty drugs, injections	-0.21	10.97	0.31
30	Non-surg supplies/devices	-0.15	5.42	0.69
31	DME	-0.24	3.86	0.37
32	Transportation	-0.31	2.51	0.11
33	Other	-0.15	5.61	0.58
	Weighted average full selection elasticity			0.49
	ϕ = derivative of profit with respect to expected spending			1.6376E-05
	σ_π = Standard deviation of individual profit			32290.64