Selection Stories: Understanding Movement Across Health Plans

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Abstract

This study assesses the factors influencing the movement of people across health plans. We distinguish three types of cost-related transitions: adverse selection, the movement of the less healthy to more generous plans; adverse retention, the tendency for people to stay where they are when they get sick; and aging in place, where lack of all movement makes plans with initially older enrollees increase in cost over time. Using data from the Group Insurance Commission in Massachusetts, we show that aging in place and adverse selection are both quantitatively important. Each can materially impact equilibrium enrollments, especially when premiums to enrollees reflect these costs.

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This study assesses the factors influencing the movement of people across employer-sponsored health plans. Such movement reflects the confluence of several phenomena: individuals differ dramatically in the expected costs they will incur; cost-related concerns make some individuals more likely to enroll in some plans than others; and the premiums that health plans receive are not tied to enrollees' characteristics.[1] Together, these phenomena imply that some plans will have to serve more expensive populations, and will therefore have to charge more, even if it costs them no more to serve any particular individual. The result is both inefficient and inequitable (Cutler and Zeckhauser, 2000). Understanding the nature and magnitude of these inefficiencies and inequities is critical if we are going to implement mechanisms to reduce them.

Risk adjustment is the most common solution economists propose for selection concerns. But risk adjustment must be based on the right model of individual choice. For example, to what extent do individuals rely on past experience as opposed to projected future experience in selecting a plan? If strongly on the latter, risk adjustment may need to be based on actual future spending experience. If factors apart from expenditures, e.g., age, have a marked effect on selection, the need for experience-based risk adjustment will diminish.

We consider a theoretical and empirical situation where there are two plans: a fee-for-service (FFS) indemnity plan and a health maintenance organization (HMO). We refer to these plans as the generous and moderate plan, where the generous plan both offers more freedom in selecting providers and costs more. The dataset used includes all medical claims for employees and their families who are employed by the state of Massachusetts and purchase health insurance through the state's Group Insurance Commission (GIC), roughly 225,000 insureds. Several

[1] A very few groups do engage in risk adjustment, i.e., basing premiums to plans on individuals' expected costs.

previous papers, including some by some of the authors, have used data from this population (Altman, Cutler and Zeckhauser, 2003; Cutler and Zeckhauser, 1998.)

Adverse selection is the common concern in such a setting (Rothschild and Stiglitz, 1976). People who expect to need a lot of care in the future might move into plans where choice of providers is greater and/or costs for care are lower, especially if they can pool with healthier people in those plans. If information is both complete and contractible, equilibrium insurance contracts will be optimal for each risk class, and premiums will vary to reflect the risk of each class. Such selection is not inefficient, but may be inequitable: the sick, already afflicted, pay more than the healthy for the same product.[2] Inefficiency results when information on individuals' risk classes is incomplete or there are constraints on using such information. In this situation, the healthy will then (inefficiently) ration their care so as to separate themselves from the sick so as to obtain a lower price.

Expectations of future spending are not the only factor influencing health plan choice. Transition costs may be important too. For example, insureds may be concerned with maintaining continuity with their physicians, or indeed even their plan. If sicker people are more hesitant about moving across plans, the result will be adverse retention: high risks will tend to stay, and only low risks will move. Theoretically, adverse retention is more of a problem for less generous plans. With no adverse retention, less generous plans lose enrollees whose expected costs rise, and gain enrollees whose expected costs fall. With adverse retention, plans keep the high cost people.

If transition costs are sufficiently high, no one would move across plans. We call this situation complete retention, or aging in place. Its effect on the levels of costs between plans

[2] That is, it is efficient given risk types. It is inefficient in that people cannot insure their risk type.

will depend on the way expected health spending increases with age. Generally, costs go up at an increasing rate with age. This implies that the plan with older enrollees will have the costs of its retained population increase more swiftly as time passes. This process can continue for a while, but ultimately, of course, people tip off the high end, through retirement or death. Thus, we would expect the "older" plan to switch and become the "younger" plan over time, albeit the cycle may be very long, and a plan may die from high costs on the path to ultimate rejuvenation.

In our empirical work, we examine the contribution of each of these three phenomena – adverse selection, adverse retention, and aging in place – to movement or lack thereof across plans, and the resulting cost implications. We find evidence that traditional adverse selection is a significant phenomenon, more important quantitatively than adverse retention. Adverse selection comes partly on the basis of expected medical spending, and partly on the basis of demographics. Older and sicker individuals move into more generous plans.

However, when premiums are heavily subsidized, adverse selection does not have a major impact on the long-term equilibrium distribution of insureds between plans. When levels of employee cost sharing are low, people do not significantly move across plans on the basis of medical spending, and the equilibrium without selection would look reasonably close to the one that comes with selection. In contrast, increases in premium cost sharing would have an enormous effect on the equilibrium. Raising the employee's share of the premium to the full additional amount of the high cost plan would reduce enrollment in the high cost plan by two-thirds. Not even eliminating spending-based adverse selection would materially change that result.

This paper proceeds as follows. We begin with a theoretical discussion of the factors that influence movement between plans. Next we discuss the data used. In the third section, we present estimated transition equations for movements between the two plans. In the fourth section, we simulate the long-run impact of different factors influencing plan choice, examine how these selection factors interact with firm policies, and compute the equilibria that result. We distill the lessons in our conclusion.

I. Theory

The traditional story of insurance selection looks at two factors: price and expected spending.[3] The price includes both the premium the individual pays to enroll in the plan, and the cost of using services. Some group health insurance programs heavily subsidize the least expensive plan and then charge 100% of the premium differential to choose a more generous plan, though other groups subsidize more expensive plans more heavily. The cost of using services may also differ across plans, and an individual may choose to switch plans if an alternative plan offers lower out-of-pocket costs.

Expected spending is also important in determining the value of a plan. An individual who expects to incur significant costs in the next period purchases the more generous of two plans; a low cost individual selects the moderate plan.[4] With people self-selecting in this way, the standard result is that the difference in average costs in the two plans will exceed the cost differential of serving the marginal person in the higher-cost plan (Cutler and Zeckhauser, 2000). This produces the inefficiency that flows from adverse selection.

[3] Other factors that may affect plan choice would not affect efficiency. For example, if personal preferences drive plan choice, e.g., some individuals merely prefer a more generous plan, and low mobility reflects happiness with one's current plan, mispricing of the two plans generates no inefficiencies. We focus on factors that do affect efficiency.

[4] Some models only have probabilistic separation, i.e., people expecting higher costs are relatively more likely to choose the high-cost plan. Results are less stark with this assumption, but still in the same direction.

To facilitate exposition, we clarify some of the assumptions behind this result. We assume that all individuals have the same utility function, which includes both their tolerance for risk, and the direct utility benefits of the generous plan, e.g., its greater flexibility in choosing a doctor. We also assume the benefits of the generous plan are increasing in one's risk, which is known by individuals *ex ante*.[5] Thus, higher risk individuals will disproportionately value the generous plan. However, the insured's premium for the generous plan is the same for all.

Thus, there will be a cutoff point for risk: all individuals above a certain risk level (or level of expected expenditure) will select the generous plan, while people below the cutoff will choose the moderate plan. This is the single (continuous) index model (Cutler and Reber, 1998). Because people who have a higher probability of being sick opt into the generous plan, that plan will cost more for the marginal person than its generosity alone would dictate. As a result, too few people enroll in the generous plan. It is even possible that the generous plan will empty completely, in what is termed an adverse selection "death spiral."

We will use the single index model as our benchmark, but some caveats should be stated. We have already left the world of first best optimal insurance behind when we assume merely two plans for a continuum of risk types. The two plan assumption fits many real world settings (including ours), but leaving administrative costs aside, many plans could coexist side-by-side. Even within the stripped down framework presented here, other plausible models can give different results. For example, in the classic model of Rothschild and Stiglitz (1976), where there are only two risk types, there will always be full insurance for the high risks, and the low risks will be constrained in the amount they purchase. Empirically, the continuous index model better fits the real world (Cutler and Reber, 1998).

[5] Having individuals differ only in the probability of getting sick simplifies the exposition. The analysis works in much the same way if differential costs once sick drive the adverse selection.

Backward looking selection. It is possible that people form their values of different plans not fully rationally, as the model suggests, but using heuristics. Salience based on past experience is a natural heuristic. An individual who has high costs because he contracts diabetes might choose the generous plan because he knows he is sick and will continue to be sick. In this case, past spending correlates with future spending, and the switching behavior is consistent with a fully rational model. But that may not be the case for a person in an auto accident, however. Someone who was in an automobile accident, but recovers fully, will have higher costs in the year of the accident, perhaps far higher than the diabetic, but his expected future costs will be far lower.[6] Yet the salience of spending may encourage permanent moves to the more generous plan. In other instances, we know that individuals tend to purchase flood insurance after a flood, presumably because the risk has become more salient (Kunreuther, 1984).

We term such behavior "backward looking" selection, in contrast to the "forward looking" selection of most models with adverse selection.[7] An equilibrium with backward-looking selection will still have inefficient pricing and sorting, because past spending correlates positively with future spending. But the price deviations between plans will be less severe than they would be with adverse selection based on accurate forward-looking expectations.

Adverse retention. In the traditional choice model, the costs of switching from one plan to another – both tangible and psychological – are assumed away. A less extreme assumption is that switching costs are the same for everyone. Even if so, such costs may increase with one's level of spending. Personal preference will also affect switching costs.

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[6] This assumes that individuals are not learning about their accident risk, i.e., that he is not at much higher future risk.

[7] Backward-looking selection likely reflects the Availability Heuristic or a close correlate – the tendency for people to overestimate probabilities of events that are easy to imagine, or that are close to previous experiences (Tversky and Kahneman, 1973).

There could be many explanations for a positive correlation between past spending and switching costs. First, individuals receiving therapy are likely to be reluctant to switch care midstream. Second, there may be considerable hassle in terms of transferring medical records, finding a new set of doctors, getting new batteries of tests, etc. Third, in a phenomenon that is well known from other fields, the individual may feel that even though the other plan would be better for him, his personal doctors are much better than the average. (Remember, also, that the individual played a role in selecting his current doctors.) The literature on status quo bias tells us in general that individuals are reluctant to switch health plans (Samuelson and Zeckhauser, 1988), or indeed switch any choices. Perhaps high medical costs, a signal of the past treatment of many or serious problems, reinforce this tendency.

The result of this correlation is adverse retention – the sicker someone is, the less likely they are to change plans. For individuals enrolled in the generous plan, adverse selection and adverse retention will have similar empirical consequences. For either reason, sicker people will be more likely to remain in the generous plan than healthier people. For individuals enrolled in the moderate plan, however, the two forces have differing implications. Adverse selection would imply that among those in the moderate plan, sicker people would be more likely to move to the more generous plan; adverse retention, by contrast, makes them more likely to remain in the moderate plan.

Aging in place. As moving costs increase, even low-risk people will be discouraged from changing plans. If moving costs were prohibitive, there would be complete retention – individuals would stay where they first land. They would then age in place, which becomes an ever increasing burden on a plan until old members retire or die. Figure 1 graphs average costs in our data by age and sex. There is a clear non-linear pattern: outside of newborns, costs increase faster as people grow older. Given the differences in demographic enrollment in our plans (discussed below), if all individuals stayed in place, the average cost differential between the FFS plan and the HMO would rise by 3.5 percent in the first year.

Individuals do not stay fixed, of course; some age out of the group. The aging out phenomenon will lead the initially expensive plan to become relatively cheaper. Ultimately, assuming no other changes, there will be a flip-flop in premiums, and new entrants will be lured to the initially older plan. This type of cycling would continue indefinitely, albeit over periods of many years, assuming that all plans survived the strain of rising premiums.

Being fed up. There is another selection possibility, which we label "fed up." It is possible that people who use great amounts of medical care experience the downsides of any medical plan – missed payments, hassles in using care, and the like. Then, following a "fed up" grass-is-greener mentality, they speculate that the other plan will be better. If they act on that supposition, high cost people in either plan will be more likely to switch.[8] Spending would offer a crude way to measure exposure to unsatisfactory encounters. A more powerful measure, which we will use, looks at billing errors. Note that the fed up phenomenon would exert an effect that is precisely the opposite to the direction of the adverse retention model.

II. Empirical Framework

Our empirical work examines how monetary costs and health spending affect plan choices, differentiating between adverse selection, adverse retention, and aging in place. Following our theoretical discussion, it is important to divide the population by initial plan

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[8] Note if individuals have some leeway in timing healthcare services, there will be cases where if a person is fed up early in a proscribed period, he will then refrain from receiving further services from that plan. An endogenous feedback effect from fedupness to low healthcare spending within that plan and period will lead to an eventual quit.

enrollment. We sort people into two initial locations: those in the FFS plan and those in the (aggregate) HMO.

Consider first an individual in the FFS plan at time t. Our model posits that he will remain in his plan if doing so offers a higher utility than moving to the HMO. Normalize his utility for the HMO to 0. His utility V – measured in dollar equivalents – for being in the FFS plan at time t+1 is:

$$V(FFS_{t+1} \mid FFS_t) = X_t\alpha + \alpha_C Copay_t + \alpha_V Visits_t + \alpha_S Spending_t + \alpha_{\hat{S}} \hat{S}pending_{t+1} + \alpha_{Prem}(Prem_{FFS} - Prem_{HMO})_{t+1} + \varepsilon.$$

(1)

Here α_S is the impact per dollar of past spending on the attractiveness of the FFS plan, and $\alpha_{\hat{S}}$ is the impact of forecasted future spending. Traditional adverse selection or adverse retention imply that $\alpha_{\hat{S}} > 0$, while backward looking selection implies that $\alpha_S > 0$. One might model adverse selection, alternatively, or in addition, as depending on the number of visits in the past, in which case $\alpha_V > 0$. For the FFS plan, adverse selection and retention work in the same way; hence they cannot be disentangled merely by looking at who moves. The vector X includes demographic factors that might influence mobility, including age, sex, and race.

There is an analogous equation for the value of the FFS plan for people currently enrolled in the HMO:

$$V(FFS_{t+1} \mid HMO_t) = X_t\beta + \beta_C Copay_t + \beta_V Visits_t + \beta_S Spending_t + \beta_{\hat{S}} \hat{S}pending_{t+1} + \beta_{Prem}(Prem_{FFS} - Prem_{HMO})_{t+1} + \nu. \quad (2)$$

The adverse selection explanation suggests that $\beta_{\hat{S}} > 0$ or $\beta_S > 0$, depending on whether selection is based on expected future spending or past spending, while the adverse retention explanation suggests the opposite. If people respond instead to increased numbers of visits in the past, the coefficient β_V will be positive (adverse selection) or negative (adverse retention).

Estimating the impact of premiums on enrollment is difficult with only one group of enrollees. Because everyone pays the same premium for the same plan in the same year, the FFS – HMO premium differential is perfectly collinear with year dummy variables. If premiums for the two plans varied greatly over time (as they do in Cutler and Reber, 1998), we could parameterize the year effects and estimate how premiums affect enrollment. But premiums in the GIC plan tend to move up and down together. As a result, rather than attempt to estimate a premium elasticity, we omit premiums from the model. In our simulations, we use a premium elasticity common to many studies in the literature: -0.5 (Cutler and Reber, 1998; Royalty and Solomon, 1999;, and Strombom, Buchmueller, and Feldstein, 2002).

III. Data

Our data includes all medical claims from fiscal years 1994-2004 for all Massachusetts state employees and their families covered by the state's health insurance system, termed the Group Insurance Commission (GIC), and for the small percentage of local employees that the GIC also covers. Employees can choose from among several HMOs, a PPO, and an FFS insurance plan. Though members have a menu offering multiple HMO plans, we care about selection due to systematic variation in plan generosity. The HMOs in the GIC all offer reasonably similar benefits, access to providers, and degree of restriction. Thus, we aggregate people in the various HMOs and the single PPO into a generic “managed care” plan, which we usually refer to as the HMO. (The PPO gets only a small percentage of the non-FFS enrollment.)

The state subsidizes all plans by paying approximately 85% of total premium costs. The percentage paid is the same across plans, thus implying that the dollar value of the state's subsidy is higher for more expensive plans. The heavy subsidization of marginal expenditures by the GIC may approximate some type of second-best cross-subsidy risk adjustment, but if true that would be fortuitous. There is nothing explicit – each plan stands nominally on its own. Moreover, it would be miraculous if 85% were the right sharing percent to get close to the optimal cross-subsidy.

Medical claims fall into three broad categories: inpatient services, outpatient services, and pharmaceutical outlays. We aggregate all claims within a year and use the year as the basic unit of observation. Changes in health plan enrollment are allowed only in a window at the beginning of each fiscal year, hence there is no problem of a person being a member of multiple plans within a single observation. To compare years, we convert spending into real dollars. All of our regressions include year dummy variables.

Since families are almost always in the same plans (other than coverage through another employer), we estimate our models at the family level. We sum spending, copays, etc. within families, and estimate the probability of a switch for a family as a whole. Demographic variables, rather than being exclusive dummy variables, count the number of people in each demographic bin.

For people who quit and change plans we only have their spending in the new plan. But our switching equations compare movers with stayers in the initial plan. The proper metric for subsequent spending is the spending that would have occurred had the person not changed plans. This produces the index problem of translating one plan's spending into the equivalent of the other. The data appendix explains how this indexed spending variable is computed. Briefly, we estimate a common price difference between managed care and the FFS insurer and use this differential to adjust spending across plans.[9]

Equations (1) and (2) enter spending in a linear way, but this may not be right. In our empirical work, we consistently use dummies for spending deciles as independent variables. A step function offers a more flexible functional form than, say, a quadratic in spending.

Figure 2 provides a broad overview of GIC population dynamics. It shows the percentage of people in the FFS plan each year, and the premium differential between the FFS plan and the HMOs.[10] Participation in the FFS drops in the early years from about 40 percent to 25, with a modest rebound starting in 2001. The reduction in FFS enrollment corresponds with a rise in the premium differential between the two plans, as theory would predict. The flattening of the loss in FFS percentage coincides with a drop in the differential in the middle years. Until 2001, we see the broad phenomenon of a higher price leading to lower enrollment. After that, we have the anomalous effect of the FFS percentage increasing alongside the premium differential in the last years. This likely reflects the general trend of dissatisfaction with HMOs spreading across the country.

Figure 3 presents the distribution of log (real) spending in the two plans, aggregated over all years. There is a large share of zero spending, with positive spending having a (roughly) log normal distribution – a well-known pattern in health care. The FFS distribution has fewer people with no spending, and a spending distribution shifted to the right of the HMO distribution.

Table 1 presents some basic summary statistics of the dataset, broken down by the two plans. Over the entire time period, the FFS plan averages about one third of the total GIC

[9] This assumes something like the higher spending we see for what is categorized as the same services across plans is due to economic rent, which is generally believed to be the case.
[10] The differential is calculated as average costs in each plan after the subsidy and a markup for administration charges.

membership. It has a much higher percentage of persons at older ages, as adverse selection would predict. The percentage of those 50 and older is 45 percent for the FFS versus 18 percent for the HMO. The difference in average age for the two plans is ten years. Computing the ratio of very young children – ages 0 to 4 – to women of ages 20 to 34, high fertility years, across the two plans we see .65 children per woman in the FFS plan and .68 children per woman in the HMOs, a very slight excess propensity in the HMO. This statistic is interesting because younger women should have less status quo bias in favor of the FFS plan and have time to change plans before birth.

Both number of visits and total copays are lower for the HMO. The exit rate is higher in the FFS plan, reflecting the plan's older population. Among entrants into the FFS plan, 35 percent are ages 50 and higher (not shown.) The corresponding number for the HMO is a mere 10 percent.

IV. Selection Results

In this section, we estimate enrollment equations (1) and (2). As a first broad overview, Figures 4(a-c) show mobility rates between plans by spending level. It also breaks out movement across the various HMOs in the system. In figure 4(a), each data point shows the share of people in that bucket in the initial year who left that plan in the subsequent year. The first observation is for people who use no services during the year; the positive spenders are divided into ten deciles from lowest to highest.[11]

There is clear evidence of adverse selection. For people initially in the HMO, transitions from the HMO to the FFS rise monotonically after the second decile. The reverse is true for

[11] To control for inflation, we calculate deciles by year within plan, and count observations within deciles accordingly.

people initially in the FFS plan: quit rates decrease with spending. Movement across HMOs, by contrast, is flat across deciles.

Figure 4(b) shows quit rate by spending in the subsequent year, after arrival in the new plan. In this chart, there is decreased mobility from one HMO to another at higher deciles, in accord with adverse retention. Other evidence supports adverse selection: people who will use a lot of care in the next year are more likely to leave the HMO for the FFS plan, and people in the FFS plan who will spend less are more likely to switch to the HMO.

Finally figure 4(c) shows the arrival rate – the share of people in each bucket who came from the other plan in the previous year. Arrival rates also produce a pattern consistent with the single index model. Subsequent spending among people who leave the HMOs tends to be at the lower end of the FFS distribution . Arrival rates into the HMO from the FFS plan are relatively flat by spending, however, with a very small uptick at the highest deciles. HMO to HMO arrival rates decrease at higher decile spending, in accord with the pattern found for departures.

While the patterns in figure 4 are consistent with adverse selection, we note that the magnitude of the effect is not particularly large. Only 2.5 percent of those in the top decile of the HMO plan move to the FFS plan, and they account for but 4 percent of the FFS enrollees. Even if all of these enrollees ended up in the top decile of the FFS plan (they assuredly do not -- see figure 4(c)), they would not add a significant amount to average FFS spending. On top of this, a relatively large share of low cost people move as well.

Figure 4 shows transition rates for the year before and after a potential move. But people might need several years of especially high or low spending before concluding that their health status merits a change in plan. And looking at spending for several years after a move tells us about whether movers gradually come to resemble the stayers in their new plan, or tend to remain an identifiable group. To examine this, we ran a regression relating spending for each person in each year on dummies for year before a quit, two years before a quit, year after a quit, etc. A separate set of dummies was created for a quit from FFS and for a quit from HMO. We control for year and plan dummy variables and basic demographics (age and sex).

Figure 5 shows relative spending in the five years before and after a plan transition, along with a 95% confidence band.[12] While there are possible attrition issues (an observation for a person 3 years before a quit means there is also an observation for that same person two years out, but not necessarily vice versa, etc.), the low turnover in the GIC suggests these are minor.

For those who will ultimately move from the FFS plan to the HMO, spending is substantially higher 3 to 5 years prior to the switch, and then drops in the two years before. Spending is slightly below average in the year just before the quit. This is consistent with healthy low spenders in the FFS plan being the ones who decide to switch – they are experiencing a sizable shift towards better health, but wait for more than a year to draw firm inferences. After the move, spending (corrected for being in the cheaper plan) is higher than those always in the HMO. This is consistent with the single index model, where people who are the less expensive in the FFS plan move to the HMO, where they are among the highest spenders.

Among those who move from the HMO to the FFS plan, spending is high prior to the move, about 10 to 20 percent higher than non-movers.[13] Spending is higher after the quit, though by only 5 to 10 percent. Thus, people who leave the HMO for the FFS plan tend to be slightly more expensive than the average FFS enrollee for a number of years.

[12] The omitted category is a person who does not move during all these periods.

[13] A possible story here is that those a year from moving may decrease their spending in anticipation of more generous case in the destination FFS plan. A paper that looks at similar issues to this one finds this behavior (Tchernis, Normand, Pakes, Gaccione, and Newhouse, 2006.)

We now turn to the transition equations proper. Table 2 reports logistic equations for movement from the HMO to the FFS plan. The first column includes demographic variables for the household, along with visits and copays in the year prior to the switch. We also include a dummy for negative total spending during the year, presumably due to billing mistakes that have not yet been fixed.[14] We fix billing mistakes as we are able (see the data appendix), but cannot offset all of them. Since we are not sure of the timing of when the misbilled health services occurred, it is simply left as a separate category.

There is also a dummy for any negative (single) charge during the year. As noted, such a charge indicates some degree of insurance problem – perhaps a reason to be fed up with one's insurer and switch plans.[15] The table reports the logit coefficients and the relative risk of switching for the associated variable.

Demography strongly affects plan mobility. Families with older members are more likely to move into the FFS plan than families with younger people. This is true for both women and men. The coefficients are large. Older men, for example, are as much as 60 percent more likely to switch plans than younger adult males.

The second column includes (indexed) subsequent year spending.[16] The inclusion of future spending is a specification of a fully rational equation. There are dummies for zero spending and each positive decile of spending (the omitted dummy is spending in the first decile).

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[14] For example, a provider might bill $12,000 for a procedure when the correct total was $10,000. There would be a subsequent claim for -$12,000, followed by a $10,000 claim. If the latter two transactions occurred in a different year from the first one, the person would have negative spending during the year.

[15] Of course, the individual might not know about this back and forth between the insurer and provider, but in many cases they will receive notice of it.

[16] Expected spending comes from our estimated spending equations shown in Appendix 1, and discussed in section V below.

The results on future spending confirm Figure 3: people in the upper decile are far more likely to switch plans than people in the lowest deciles. The effect is monotonic in spending and large: those at the top of the spending distribution are over 90 percent more likely to switch plans than those at the bottom of the distribution. Having additional visits has little effect on plan mobility, indeed switching signs across different specifications. The coefficient on out-of-pocket payments is statistically significant, but small: a $100 increase in copays increases the probability of switching to the FFS plan by 0.2 percent. People with negative claims during the past year are less likely to switch to the FFS, evidence against the idea that people fed up with errors switch plans.

The third column uses past spending instead of future spending to predict mobility. Zero past spending has a substantial positive effect on quits (34 percent higher relative risk), as does very high past spending (77 percent higher relative risk).

In column 4 we estimate all these variables simultaneously. The major change with all covariates included is the effect of previous spending largely goes away or even reverses sign. In a measure of seeming rationality, people do not look solely at past spending when they make decisions to switch insurance plans. Importantly, demographic variables and expected future spending are essentially unchanged in the full specification. People (and their families) move into the fee for service plan when they are older, and when they suspect they will be high cost in the future. These results are consistent with the adverse selection explanation, and reject the adverse retention hypothesis. Interestingly, our results reject a pure adverse selection story that only future spending matters. Other factors, notably demographics, matter as well

Table 3 repeats the analysis in Table 2, considering movement from the FFS plan to the HMOs. The number of visits in the previous year has an effect similar to that found in Table 2.

Larger copays slightly raise the quit rate, but again the effect is not large. Having had any negative claims positively affects mobility, consistent with being fed up.

Turning to the spending and demographics, we find that demographics are again extremely important. Older people are significantly less likely to leave the FFS than are younger people. The difference between prime age and older individuals is about 50 percent. High future and past spenders are less likely to leave the FFS plan, though past spending seems to matter more than future spending for this group.

Overall, tables 2 and 3 favor adverse selection over adverse retention. Recall the key prediction to differentiate the two: adverse selection implies that high cost people in the HMO should be more likely to switch to the FFS plan, while adverse retention implies that they should be less likely to switch. As table 2 shows, high future spenders and older individuals are more likely to switch plans.

An alternative way to gauge the importance of selection and retention is to compare people who have been in the GIC with new entrants. New entrants, by definition, are not tied to any plan in the GIC. Though they may have been enrolled in an equivalent to one of the plans in a previous job, the new entrants will at least have to choose a new plan within this group. That is, there are positive costs of choosing any plan.

The first column of Table 4 shows the plan choices of new entrants. Demographics remain important; older entrants are much less likely to sign up for the HMO than the FFS plan. The future spending variables suggest only limited selection based on future costs. Zero spenders select the HMO more often, as one would expect. Medium spending deciles have rates higher into the HMO though this flattens at upper deciles. Surprisingly, high spenders are not more likely to join the FFS plan.

V. The Dynamics of Plan Choice

We are interested in how plan decisions translate into enrollments in the two plans over time, in both the short and long run. Tables 2 and 3 show the single period transitions, but they need to be iterated over time to see long-term dynamics. Because the equations are not linear, there is no closed-form solution to such a system. A simulation model, however, can yield clear results. We thus simulate the long-run equilibrium implied by these equations.

Our simulation model has three parts. The first part, presented above, is the relationship between spending, demographics, and plan transitions. The second part of the model addresses the evolution of individual spending over time. The third part of the model relates copayments and the number of visits in a year to spending in that year.

The dynamics of individual spending are estimated using a conventional two-part model: a logit equation to determine whether the individual has positive spending, and a second stage linear regression for the logarithm of spending conditional on positive amounts. The first two columns of Appendix Table 1 report the logit equation for whether the person had positive spending, separately for HMO and FFS enrollees. Higher previous year visits and copays increase the probability of positive spending, as does being older (holding past spending constant). People in the HMO plan are marginally less likely to have positive spending. Higher lagged spending increases the probability of positive spending, with some drop-off at the very highest levels.

The equations for conditional use appear in the last two columns of the table. Spending rises with age among positive spenders for both plans. Women spend more than men in all age groups but the highest. Higher previous-year spending strongly predicts higher current spending.

The third part of the model predicts copays and the number of visits, based on demographics and spending in that year. These equations are not particularly important in the estimated transitions, but are required for the simulation model. The first column of Appendix Table 2 shows a sizable coefficient on lagged visits, indicating a fair amount of persistence. Older people have more visits, along with women of child bearing age. People in the HMO have on average seven percent fewer visits than those in the FFS plan holding other factors constant.

The second column regresses the logarithm of copayments on the contemporaneous number of visits and spending for the year. If copays were just a flat fee per visit or a simple formula based on total spending then this regression would explain all of the variance. As it is, the R^2 is high: .67. Total copays are positively influenced both by number of visits and total spending during the year. Surprisingly HMO copays are 20 percent higher than for the FFS plan, controlling for these other variables.

To simulate the equilibrium, we draw a random sample of people from our dataset. Using the base year data (1998), we simulate subsequent spending, copayments, and number of visits. We then sum the results for hypothetical families. Average premiums are based on costs, plus a 10 percent administrative load. We use the initial GIC subsidy of 85 percent, and explore other variations. The individual predictions and estimated premiums then feed into the transition equations. Where we have probabilistic equations (for example, quits), we first calculate the family's logistic cutoff point, and then draw a standard uniform random variable to determine the outcome. For most sets of assumptions about the structure of our model, this process reaches a steady state – or more accurately, given the randomness, proceeds to a central tendency.[17] To

[17] Empirically in all cases we reached a steady state, usually relatively quickly.

avoid random outcomes, we average over the final 100 periods at the end to get the long-run estimate.

Table 5 shows the simulation results. Our first simulations use a static population: no one ages, dies, enters or departs. We do this to factor out the influence of changing demographics on the steady state. The first column reports the results using a 15 percent individual share of the premium – the current GIC sharing rule. The remaining columns show what happens if that share is increased to 50 and 100 percent.

The first row is the baseline share in the FFS plan, 28 percent. Running the current model forward, we predict an equilibrium FFS share of 30 percent, shown in the second row. This is close to the current value, suggesting that the GIC is currently near steady state. Figure 6 shows the transition dynamics. The enrollment increase effectively happens within 15 years.

The next two rows examine the importance of selection. The third row removes any impact of past and future spending on the decision to change plans, thereby ruling out adverse selection and adverse retention. In equilibrium, this lowers FFS enrollment to 25 percent. As Figure 6 shows, this is a gradual change. Looking at the next two rows, which turn off future and past spending separately, we see that eliminating traditional adverse selection is the explanatory factor that accounts for the overall spending effects. Extrapolation from past spending has basically no effect on enrollment. The reason why adverse selection raises enrollment in the FFS plan has to do with the demographics of the population. Relatively few young people are in the FFS plan, while a number of old people are in the HMO. When those old people become sick, they transfer into the FFS plan, without a large offsetting outflow. Eliminating this impact lowers enrollment in the FFS plan.

The final simulation examines the impact of complete retention, i.e., no one switches plans but people do age. To examine such aging in place, we need to add even more dynamic structure. Each year, we increase everyone's age by a year. We then use a logit equation to estimate the probability that a person leaves the GIC. This logit equation is shown in the second column of table 4. As expected, age is the strongest predictor of group exit. Higher spenders are less likely to leave the group than are lower spenders. We then hold the total population constant by drawing entrants from our database to just equal the numbers of those who exit. We iterate the model to find the steady state.

As Figure 6 and Table 5 show, enrollment in the FFS plan falls to 19 percent over time. The drop in FFS enrollment is due to both the differentially older folks in the FFS exiting and the relatively young entrant population, which tends to prefer the HMO. In the aging scenario, the plans will cycle in and out of prominence. As the FFS plan enrollees retiree, the plan will fall in cost relatively, and more people will enroll in it. Figure 6 shows that this effect is not prominent. Attachments to the FFS and HMO plans are relatively large, and so cycles are minimal.

All told, selection effects given the current premium structure affect the equilibrium only slightly, in large part because the insured pays such a small proportion of the marginal cost. At the current 85 percent subsidy, we estimate that equilibrium enrollment in the FFS plan is 30 percent. If the GIC reduced its subsidy to 50 percent of the premium differential, in contrast, the effect would be immense. We estimate that enrollment in the FFS plan would fall to 13 percent in that scenario. If the employee had to pay the entire marginal cost of the FFS plan, we estimate FFS enrollment at only 8 percent. Because of selection, this reduced enrollment would bring with it a very large increase in FFS premiums.

V. Conclusions

Pooling of heterogeneous individuals into several health plans can lead to a variety of different equilibria, depending on the nature of selection. Examining data from the GIC, we show that adverse selection substantially outweighs adverse retention. Despite a low rate of overall plan switching, the switching that does occur is concentrated among the older and less healthy individuals. As a result, the indemnity plan is always selected against.

Still, these effects are small relative to the impact of changes in the mix of employer and employee premium payments. Moving from an 85-15 sharing rule to one where the employee pays the marginal cost of the more generous plan would reduce enrollment in the FFS plan by two-thirds. Given the high premium that results, it is entirely possible that an adverse selection death spiral would set in, and the generous FFS plan would ultimately no longer be available. Premium structures are important, especially as they interact with selection behavior.

Our results raise two questions. The first question is how to compare our results with those from other groups such as Harvard University, where adverse selection has proven to be very important. We suspect that there is a salience feature at work. When premiums change suddenly, people are induced to think about their health plan choice. Since this thinking works along adverse selection lines, big system changes tend to cause greater instability.

Our results also have implications for risk adjustment. The fact that selection based on future spending is not a particularly strong feature explaining plan mobility suggests that ex post experience – which the GIC essentially uses – need not be part of an optimal risk adjustment system. What is particularly important is to adjust for demographics; age and sex explain enormous spending differentials as well as plan mobility decisions. Such easy adjustment strikes a note of optimism about the ability to have a competitive choice process for health insurance.

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Data Appendix

We restrict our sample to working individuals and their families by limiting ages included to 65. We allot our population into demographic groups for males and females of ages 0 to 4, 5 to 19, 20 to 34, 35 to 49, 50 to 60, and 61 to 65. Where we have a break in plan enrollment of less than 3 months and the person rejoins the same plan we assume a clerical error has occurred, and assign the person to have been continuously in that plan. For later years (2000-2004), to preserve confidentiality, we are only given a person's birth year. We assume the middle of the fiscal year as the birthday from which to calculate age. Our visits variable is for outpatient visits only.

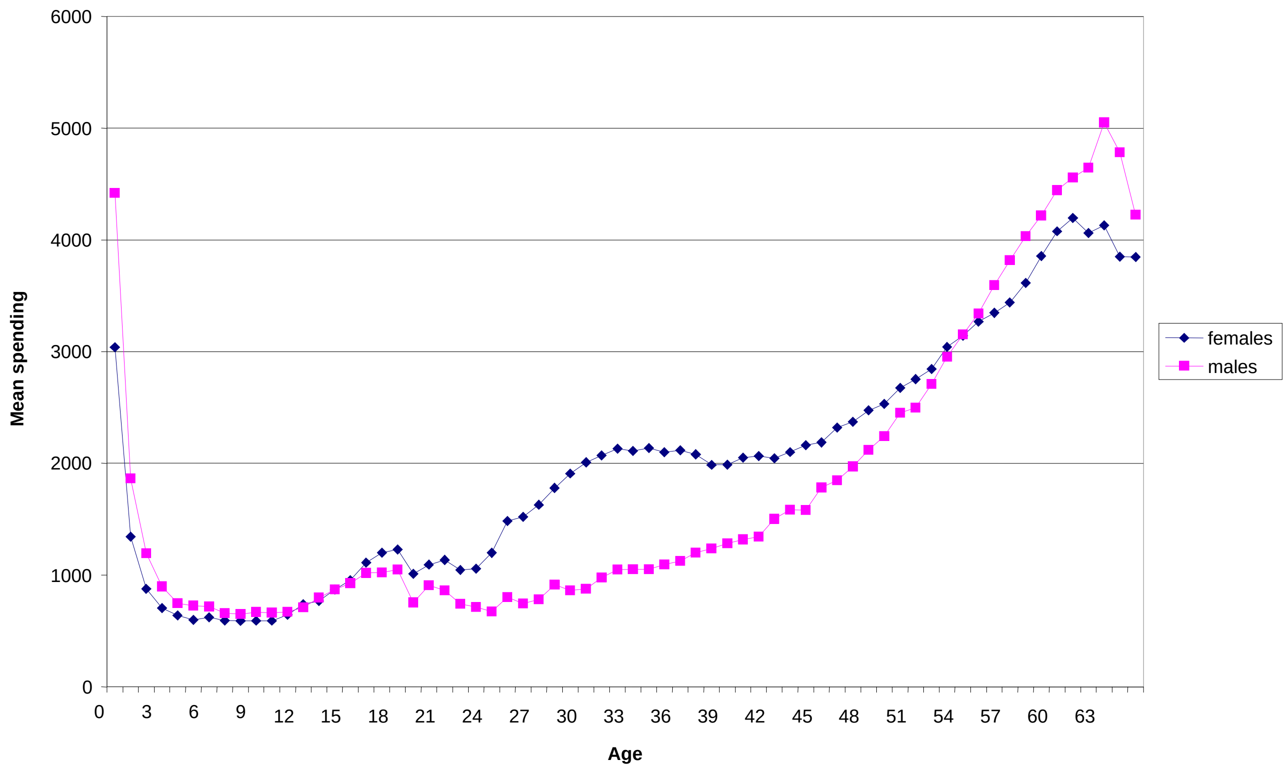
With medical claims data there are cases where a billing mistake has been made and a second, offsetting, negative charge record is later created. Though we aggregate within a year, there are still occasions where this does not correctly nullify these charges (i.e., when the positive and negative charges are not within the same year.) To attempt to correct for this, for each person we take all their claims in three-year windows to attempt to find offsetting positive and negative charges. This affected only a very small number of observations.

Our cross-plan indexing procedure is the following. We have medical procedural codes (classification systems ICD-9 and CPT) for many claims. Where there exists a procedural code match across plans, we impute the mean spending on a procedural code in one plan to be what it would have cost in the other. This leaves us with the problem of observations missing a matching procedural code. What we have done is find a mean difference between the two plans by running a regression, on the observations that matched, of one plan's actual spending on the imputed mean spending (in logs, with year dummies, and weighted by the number of observations used in calculating the mean.) The coefficient on imputed spending in this regression was then used to multiply non-matching observations to give them an imputed value. (Note in general all cross-plan spending comparisons always have the question of spending reflecting differences in health status versus one plan, for the same medical condition, providing more services or charging higher prices for the same condition). An earlier paper (Altman, Cutler, and Zeckhauser, 2003) addressing this issue with GIC data found a higher price charged by the FFS plan was part of the differential, while a different mix of services was not.)

For our logistic equation results, as well as for showing coefficients and standard errors, we present the relative risk of the associated variable: the changed probability if the variable is increased divided by the base mean probability. For continuous variables we multiply the coefficient times one standard deviation of the variable in calculating the changed probability. For visits this is 9.5 and for copays $151.[18] Among demographic variables the omitted category is males, ages zero to four. For our step function of spending we have categories of: negative spending, zero spending, and then deciles of positive spending. The left out category for spending is the first decile. One final variable is a dummy for whether the individual had at least one negative claim (rather than total spending for the year). This helps capture any problems with billing that lead to a switch, one measure of our fed up hypothesis.

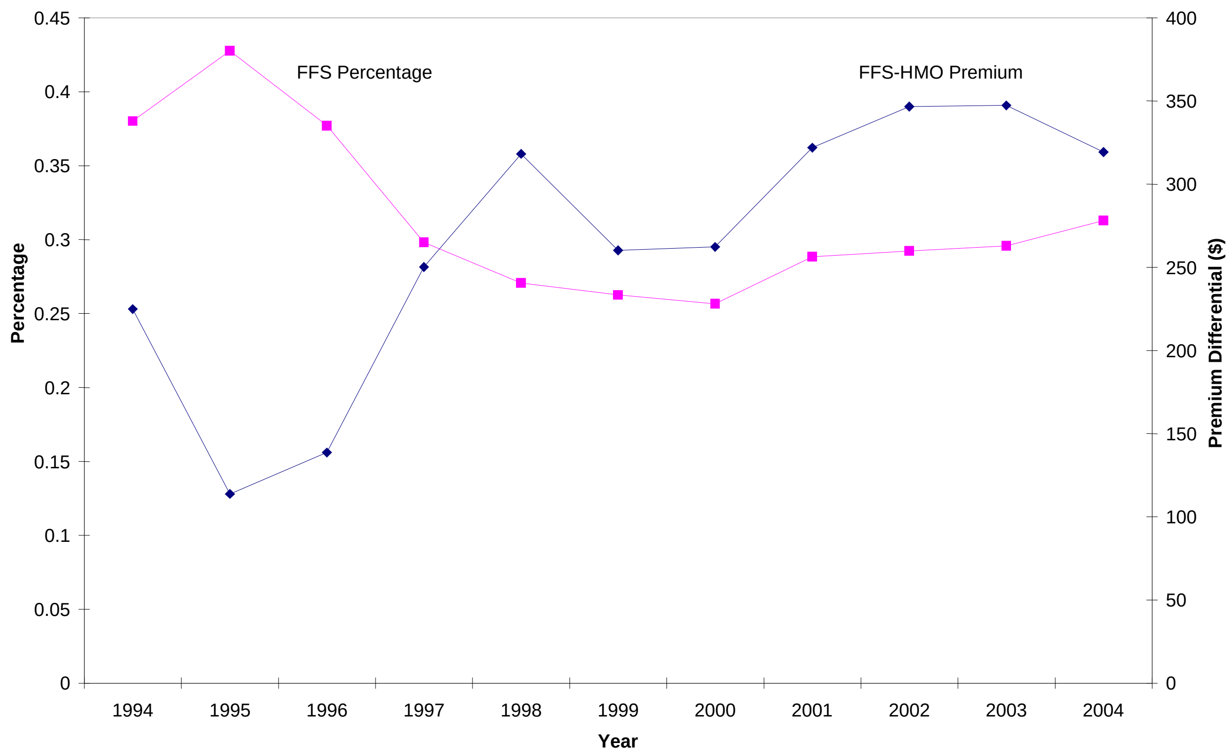
[18] For copays we're using the standard deviation of 5-95% Winsorized mean, since the raw standard deviation is an uninterestingly high $993.

Figure 1: Average spending by age/sex



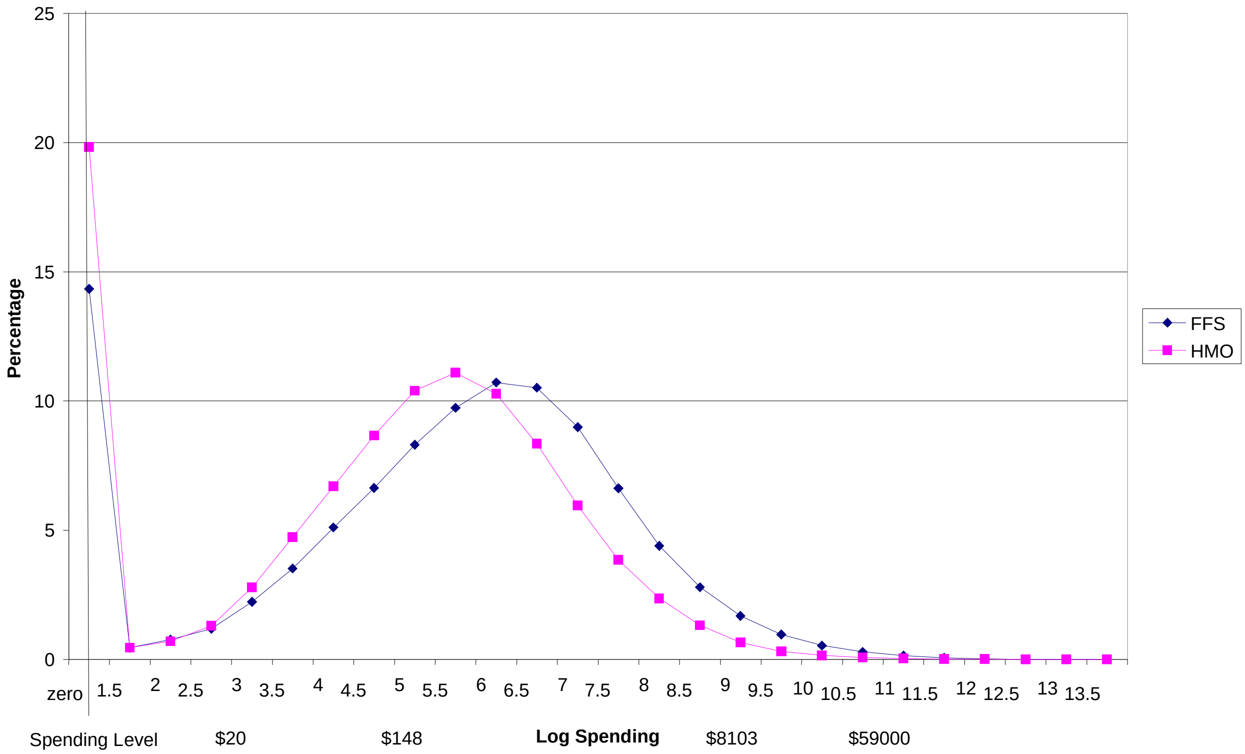
Note: Average spending is adjusted to a common year using the GDP deflator.

Figure 2: FFS Percentage and Difference in Premiums



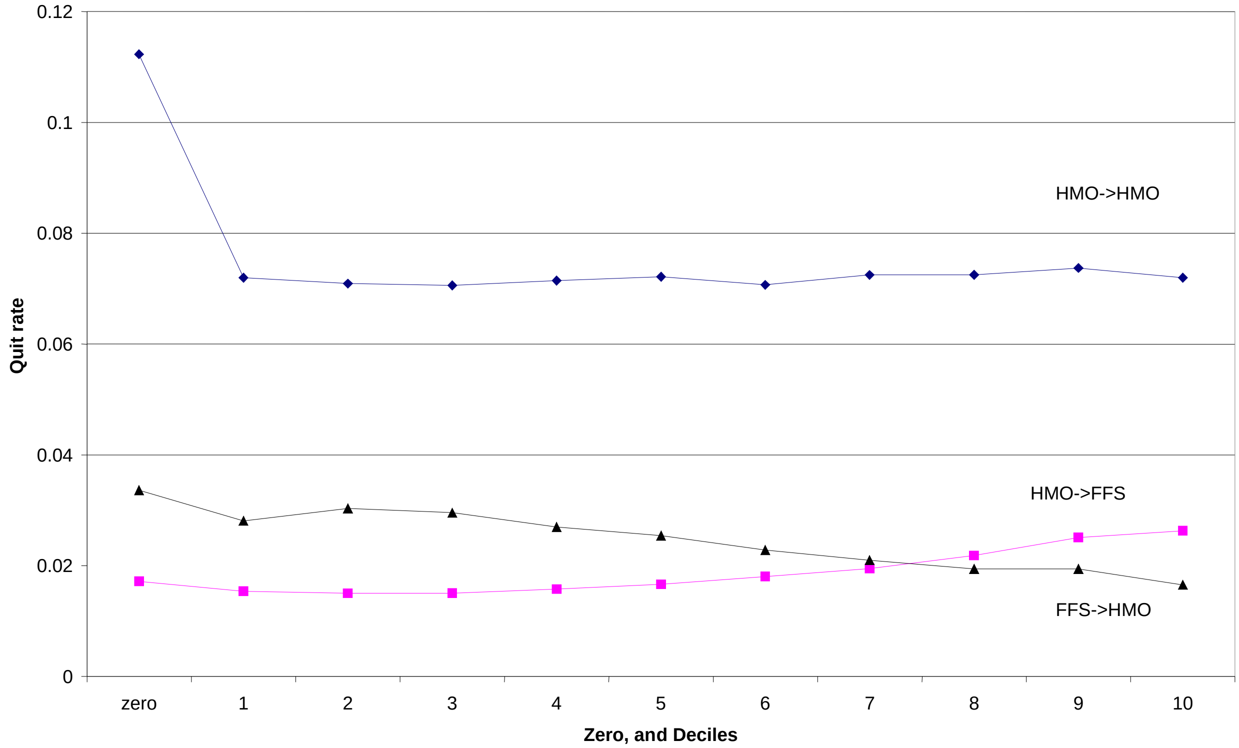
Note: The FFS plan percentage of all members is on the left scale. The difference between average FFS and HMO spending is on the right scale.

Figure 3: Log Spending, by plan

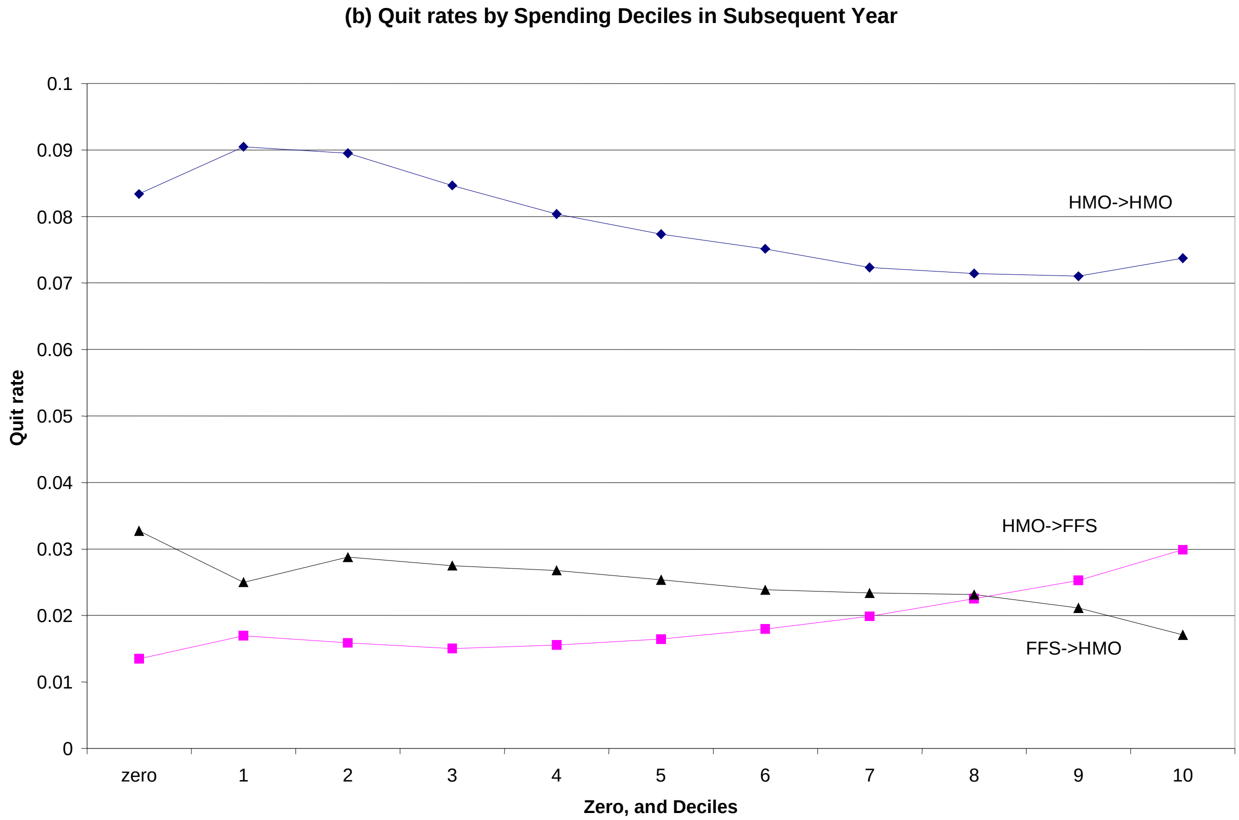


Note: Spending is in constant dollars, adjusted using the GDP deflator. For reference, several representative numbers in dollars are reported.

Figure 4(a): Quit rates by Spending Deciles in Base Year

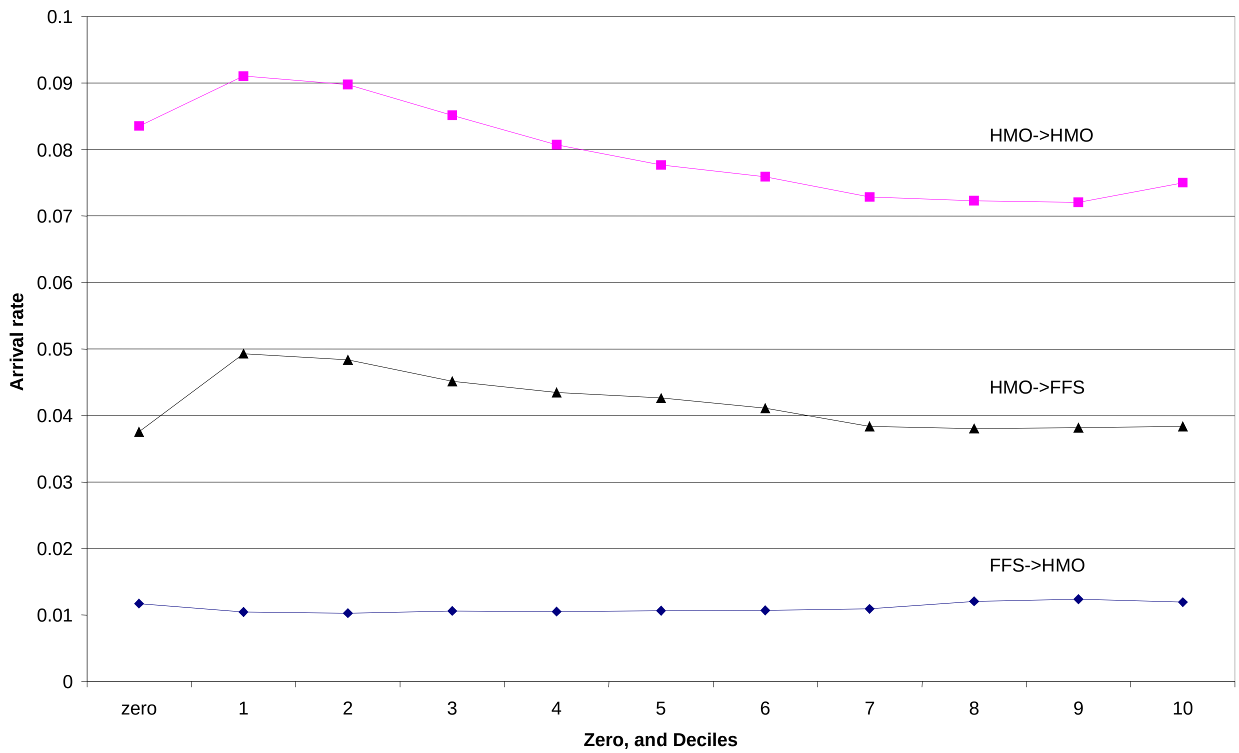


Note: There are 289,301 observations in the HMO with zero spending, and each decile has about 124,000. There are 97,133 observations in the FFS plan with no spending and each decile has about 57,000 observations.



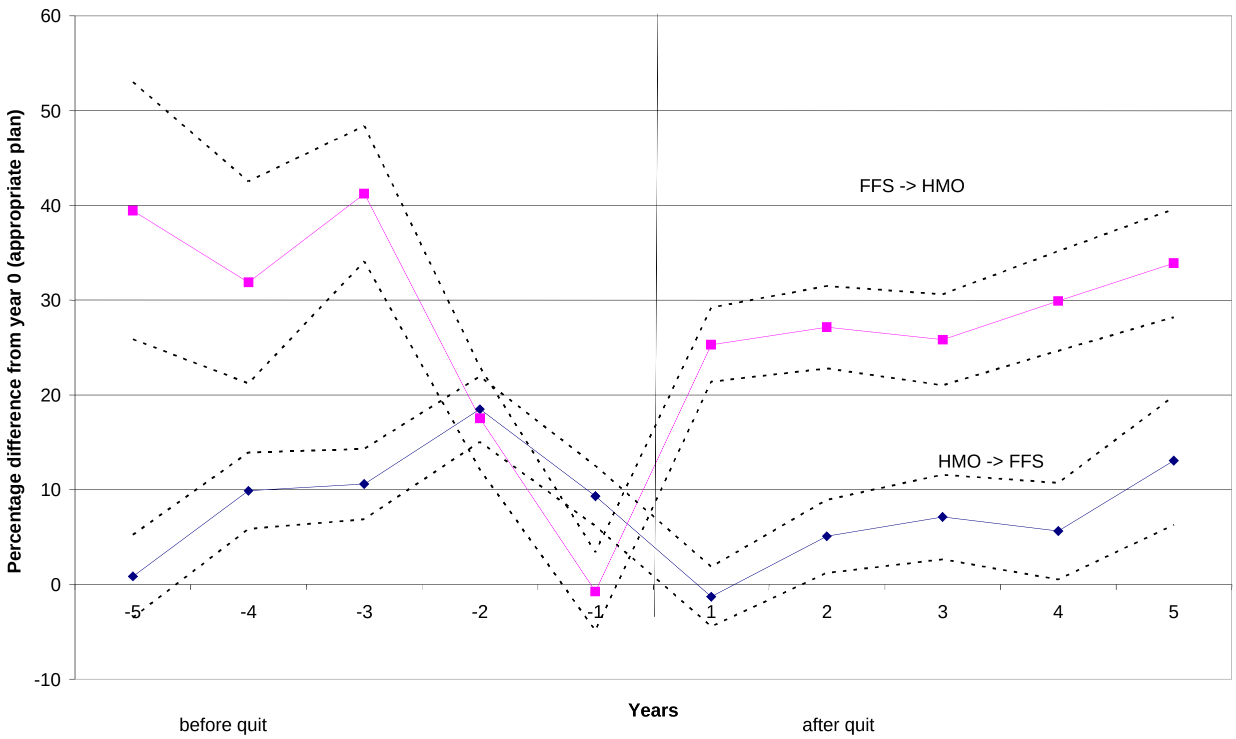
Note: There are 254,965 observations in the HMO with zero spending, and each decile has about 128,000. There are 91,132 observations in the FFS plan with no spending, and each decile has about 58,000 observations.

(c) Arrival rates by Spending Decile in Subsequent Year



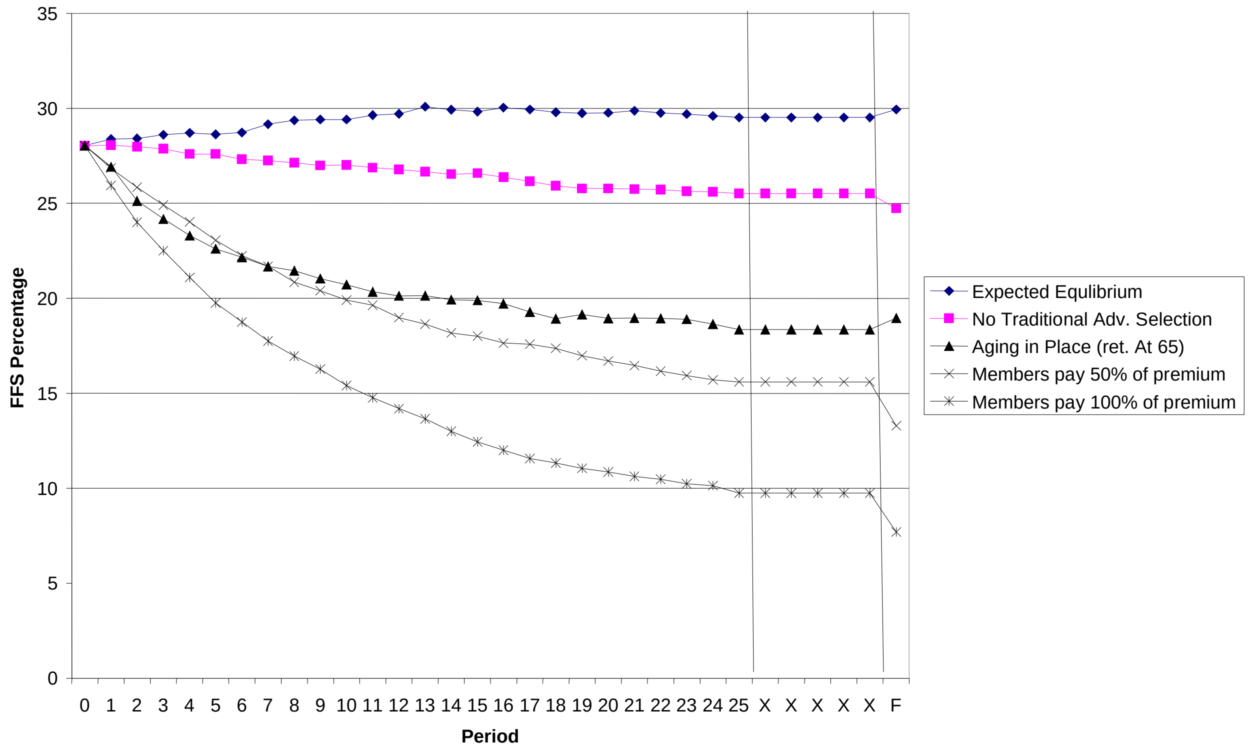
Note: There are 254,512 observations in the HMO with zero spending, and each decile has about 120,000. There are 91,5903 observations in the FFS plan with no spending. and each decile has about 59,000 observations.

Figure 5: Spending before/after quit
(with 95% confidence bands)



Note: The omitted category is members who did not move during all these periods. For example, -1 represents the year before the switch, +1 represents the year after the switch, etc.

Figure 6: FFS percentage dynamics



Notes: The five periods labeled “X” before the last point are just kept at period 25 for visual convenience. The last point labeled “F” is the final equilibrium.

Table 1: Summary Statistics for Plan Mobility Data

	FFS Plan (32%)		HMOs (68%)	
Measure	Mean	Standard Deviation	Mean	Standard Deviation
Age (years)	41.6	19.0	31.7	18.0
Spending (dollars)	$2,974	$10,945	$1,548	$6,647
Copay (dollars)	$154	$297	$118	$1186
Visits (number)	7.2	11.2	5.7	8.5
Percent Positive Spending	86%		81%	
Entrant Rate	12%		11%	
Exit Rate	17%		10%	
Quit Rate	3%		2%	
Male 0-4	2%		4%	
Male 5-19	8%		13%	
Male 20-34	5%		8%	
Male 35-49	10%		14%	
Male 50-60	12%		7%	
Male 61-65	7%		2%	
Female 0-4	2%		4%	
Female 5-19	8%		12%	
Female 20-34	6%		11%	
Female 35-49	14%		17%	
Female 50-60	17%		8%	
Female 61-65	10%		2%	

Note: Data are for the Group Insurance Commission and are averages for all years 1994-2004.

Table 2: Logistic Regressions for Plan Switching From HMO to FFS

	Demographics		Future Spending		Past Spending		All	
Variable	Coefficient	Relative Risk	Coefficient	Relative Risk	Coefficient	Relative Risk	Coefficient	Relative Risk
Intercept	-3.491***		-4.033***		-4.109***		-3.754***	
	(0.035)		(0.045)		(0.042)		(0.052)	
Visits	0.005***	1.10	-0.005***	0.91	-0.005***	0.91	-0.001	0.99
	(0.001)		(0.001)		(0.001)		(0.001)	
Copay	0.000	1.00	0.000**	1.00	0.000**	1.00	-0.000***	0.94
	(0.000)		(0.000)		(0.000)		(0.000)	
Any negative	-0.135***	0.88	-0.231***	0.79	-0.193***	0.83	-0.194***	0.83
Claims	(0.019)		(0.020)		(0.020)		(0.021)	
Demographics								
Male 0-4	-0.104***	0.90	---		---		-0.190***	0.83
	(0.035)						(0.036)	
Male 5-19	-0.123***	0.89	---		---		-0.142***	0.87
	(0.017)						(0.018)	
Male 20-34	-0.456***	0.64	---		---		-0.415***	0.67
	(0.026)						(0.026)	
Male 35-49	-0.382***	0.69	---		---		-0.344***	0.71
	(0.021)						(0.021)	
Male 50-60	-0.194***	0.83	---		---		-0.198***	0.82
	(0.021)						(0.021)	
Male 61-65	0.276***	1.31	---		---		0.250***	1.28
	(0.027)						(0.027)	
Female 0-4	-0.134***	0.88	---		---		-0.214***	0.81
	(0.037)						(0.037)	
Female 5-19	-0.103***	0.90	---		---		-0.122***	0.89
	(0.018)						(0.018)	
Female 20-34	-0.379***	0.69	---		---		-0.339***	0.72
	(0.023)						(0.023)	
Female 35-49	-0.232***	0.80	---		---		-0.194***	0.83
	(0.019)						(0.020)	
Female 50-60	-0.034*	0.97	---		---		-0.013	0.99
	(0.018)						(0.019)	
Female 61-65	0.604***	1.80	---		---		0.648***	1.87
	(0.022)						(0.022)	
Expected future spending (omitted category is the first decile – lowest positive spending)								
Negative spending	---		-1.491**	0.23	---		-1.498**	0.23
			(0.710)				(0.710)	
Zero spending	---		-0.182***	0.84	---		-0.374***	0.69
			(0.042)				(0.044)	
Second decile	---		-0.019	0.98	---		0.041	1.04
			(0.042)				(0.042)	
Third decile	---		0.032	1.03	---		0.130***	1.14
			(0.041)				(0.042)	

Table 2 (continued)

Variable	Demographics Coefficient	Demographics Relative Risk	Future Spending Coefficient	Future Spending Relative Risk	Past Spending Coefficient	Past Spending Relative Risk	All Coefficient	All Relative Risk
Fourth decile	---		0.096**	1.10	---		0.223***	1.24
			(0.041)				(0.042)	
Fifth decile	---		0.141***	1.15	---		0.284***	1.32
			(0.041)				(0.043)	
Sixth decile	---		0.187***	1.20	---		0.341***	1.39
			(0.041)				(0.043)	
Seventh decile	---		0.311***	1.35	---		0.456***	1.56
			(0.041)				(0.043)	
Eighth decile	---		0.389***	1.46	---		0.537***	1.68
			(0.041)				(0.043)	
Ninth decile	---		0.571***	1.74	---		0.748***	2.06
			(0.040)				(0.042)	
Tenth decile	---		0.658***	1.89	---		0.728***	2.02
(highest spending)			(0.041)				(0.043)	
Past spending (omitted category is the first decile – lowest positive spending)								
Negative spending	---		---		-0.071	0.93	-0.251	0.78
					(0.384)		(0.387)	
Zero spending	---		---		0.303***	1.34	0.261***	1.29
					(0.035)		(0.037)	
Second decile	---		---		-0.154***	0.86	-0.275***	0.76
					(0.038)		(0.039)	
Third decile	---		---		-0.020	0.98	-0.198***	0.82
					(0.038)		(0.039)	
Fourth decile	---		---		0.018	1.02	-0.186***	0.83
					(0.037)		(0.039)	
Fifth decile	---		---		0.034	1.03	-0.221***	0.81
					(0.039)		(0.041)	
Sixth decile	---		---		0.138***	1.14	-0.152***	0.86
					(0.040)		(0.042)	
Seventh decile	---		---		0.208***	1.22	-0.089**	0.92
					(0.039)		(0.042)	
Eighth decile	---		---		0.263***	1.29	-0.110**	0.90
					(0.043)		(0.046)	
Ninth decile	---		---		0.316***	1.36	-0.030	0.97
					(0.044)		(0.048)	
Tenth decile	---		---		0.589***	1.77	0.080	1.08
(highest spending)							(0.050)	
N	704,870		705,634		706,831		704,870	
-2 Log L	140,666		143,397		143,836		139,550	

Notes: Logit models include year dummy variables. Standard errors in parentheses.
***1% statistical significance, **5% statistical significance, *10% statistical significance

Table 3: Logistic Regressions for Switching from FFS to HMO

Variable	Demographics Coefficient	Demographics Relative Risk	Future Spending Coefficient	Future Spending Relative Risk	Past Spending Coefficient	Past Spending Relative Risk	All Coefficient	All Relative Risk
Intercept	-4.129***		-3.727***		-3.591***		-4.067***	
	(0.038)		(0.054)		(0.047)		(0.064)	
Visits	-0.014***	0.77	-0.006***	0.90	0.001	1.02	-0.004***	0.93
	(0.001)		(0.001)		(0.001)		(0.001)	
Copay	0.000**	1.03	0.000***	1.00	0.000***	1.00	0.000***	1.03
	(0.000)		(0.000)		(0.000)		(0.000)	
Any negative	0.044	1.04	0.087***	1.09	0.182***	1.19	0.161***	1.17
Claims	(0.029)		(0.029)		(0.030)		(0.030)	
Demographics								
Male 0-4	0.344***	1.40	---		---		0.396***	1.47
	(0.034)						(0.034)	
Male 5-19	0.114***	1.12	---		---		0.147***	1.15
	(0.021)						(0.021)	
Male 20-34	0.470***	1.58	---		---		0.476***	1.59
	(0.027)						(0.027)	
Male 35-49	0.234***	1.26	---		---		0.226***	1.25
	(0.024)						(0.024)	
Male 50-60	-0.030	0.97	---		---		-0.025	0.98
	(0.023)						(0.023)	
Male 61-65	-0.025	0.98	---		---		-0.013	0.99
	(0.035)						(0.035)	
Female 0-4	0.289***	1.33	---		---		0.334***	1.38
	(0.036)						(0.036)	
Female 5-19	0.097***	1.10	---		---		0.127***	1.13
	(0.021)						(0.021)	
Female 20-34	0.569***	1.74	---		---		0.578***	1.75
	(0.023)						(0.023)	
Female 35-49	0.294***	1.33	---		---		0.302***	1.34
	(0.021)						(0.022)	
Female 50-60	0.007	1.01	---		---		0.014	1.01
	(0.023)						(0.023)	
Female 61-65	-0.414***	0.67	---		---		-0.454***	0.64
	(0.032)						(0.032)	
Expected future spending (omitted category is the first decile – lowest positive spending)								
Negative spending	---		0.458	1.56	---		0.160	1.17
			(0.418)				(0.425)	
Zero spending	---		0.085*	1.09	---		-0.087	0.92
			(0.051)				(0.054)	
Second decile	---		-0.044	0.96	---		-0.016	0.98
			(0.057)				(0.058)	
Third decile	---		0.069	1.07	---		0.1145**	1.12
			(0.055)				(0.056)	

Table 3 (continued)

Variable	Demographics Coefficient	Demographics Relative Risk	Future Spending Coefficient	Future Spending Relative Risk	Past Spending Coefficient	Past Spending Relative Risk	All Coefficient	All Relative Risk
Fourth decile	---		-0.003	1.00	---		0.055	1.05
			(0.055)				(0.058)	
Fifth decile	---		0.073	1.07	---		0.134**	1.14
			(0.055)				(0.058)	
Sixth decile	---		0.074	1.08	---		0.134**	1.14
			(0.055)				(0.058)	
Seventh decile	---		0.074	1.07	---		0.120**	1.12
			(0.055)				(0.058)	
Eighth decile	---		0.020	1.02	---		0.047	1.05
			(0.056)				(0.059)	
Ninth decile	---		-0.020	0.98	---		-0.045	0.96
			(0.057)				(0.060)	
Tenth decile	---		-0.199***	0.82	---		-0.186***	0.83
(highest spending)			(0.059)				(0.061)	
Past spending (omitted category is the first decile – lowest positive spending)								
Negative spending	--							
-			---		-0.447	0.65	-0.534	0.59
					(0.415)		(0.418)	
Zero spending	---		---		-0.072	0.93	0.176***	1.19
					(0.046)		(0.047)	
Second decile	---		---		-0.198***	0.82	-0.159***	0.86
					(0.055)		(0.058)	
Third decile	---		---		-0.076	0.93	-0.079	0.93
					(0.053)		(0.057)	
Fourth decile	---		---		-0.228***	0.80	-0.297***	0.75
					(0.052)		(0.056)	
Fifth decile	---		---		-0.312***	0.74	-0.377***	0.69
					(0.055)		(0.060)	
Sixth decile	---		---		-0.354***	0.71	-0.454***	0.64
					(0.055)		(0.060)	
Seventh decile	---		---		-0.389***	0.68	-0.558***	0.58
					(0.053)		(0.058)	
Eighth decile	---		---		-0.482***	0.62	-0.596***	0.56
					(0.056)		(0.063)	
Ninth decile	---		---		-0.574***	0.57	-0.703***	0.50
					(0.059)		(0.064)	
Tenth decile	---		---		-0.754***	0.48	-0.793***	0.46
(highest spending)					(0.066)		(0.066)	(0.070)
N	371,888		371,922		372,616		371,888	
-2ln(L)	76,130		78,643		78,531		75,742	

Notes: Logit models include year dummy variables. Standard errors in parentheses.
***1% statistical significance, **5% statistical significance, *10% statistical significance

Table 4: Plan Choice Among New Entrants and People Exiting

	New Entrants (FFS=1; HMO=0)		Leaving GIC (Exit=1; Remain=0)	
Variable	Coefficient	Relative Risk	Coefficient	Relative Risk
Intercept	-1.051***		-1.583***	
	(0.029)		(0.014)	
Visits	---		-0.039***	0.72
			(0.001)	
Copay	---		.00**	1.00
			(0.00)	
FFS	---		0.536***	1.57
			(0.004)	
Demographics (omitted category is Male 0-4)				
Male 5-19	0.193**	1.13	-0.341***	0.74
	(0.023)		(0.013)	
Male 20-34	-0.032	0.98	0.328***	1.32
	(0.023)		(0.013)	
Male 35-49	0.295***	1.20	-0.493***	0.64
	(0.022)		(0.013)	
Male 50-60	1.183***	1.84	-0.572***	0.60
	(0.025)		(0.014)	
Male 61-65	2.040***	2.33	0.909***	2.10
	(0.036)		(0.014)	
Female 0-4	-0.058**	0.96	-0.059***	0.95
	(0.025)		(0.016)	
Female 5-19	0.222***	1.15	-0.371***	0.72
	(0.023)		(0.013)	
Female 20-34	-0.041**	0.97	0.580***	1.63
	(0.021)		(0.013)	
Female 35-49	0.499***	1.35	-0.231***	0.81
	(0.021)		(0.017)	
Female 50-60	1.482***	2.03	-0.313***	0.76
	(0.023)		(0.014)	
Female 61-65	2.229***	2.42	0.962***	2.18
	(0.033)		(0.014)	
Spending (omitted category is the first decile – lowest positive spending)				
Negative spending	-3.525***	0.04	-0.167**	0.86
	(0.713)		(0.070)	
Zero spending	-0.789***	0.56	-0.673***	0.54
	(0.019)		(0.007)	
Second decile	-0.088***	0.94	-0.397***	0.70
	(0.022)		(0.008)	
Third decile	-0.195***	0.88	-0.603***	0.58
	(0.022)		(0.008)	
Fourth decile	-0.296***	0.82	-0.795***	0.48
	(0.022)		(0.009)	

Table 4 (continued)

Variable	New Entrants (FFS=1; HMO=0) Coefficient	Relative Risk	Leaving GIC (Exit=1; Remain=0) Coefficient	Relative Risk
Fifth decile	-0.339***	0.79	-0.964***	0.41
	(0.022)		(0.009)	
Sixth decile	-0.398***	0.76	-1.094***	0.37
	(0.022)		(0.010)	
Seventh decile	-0.418***	0.75	-1.225***	0.32
	(0.022)		(0.010)	
Eighth decile	-0.375***	0.77	-1.367***	0.28
	(0.022)		(0.011)	
Ninth decile	-0.376***	0.77	-1.446***	0.26
	(0.022)		(0.013)	
Tenth decile	-0.517***	0.69	-1.153***	0.35
(highest spending)	(0.022)		(0.014)	
N	279,466		2,524,886	
-2ln(L)	299,934		1,692,464	

Notes: Regressions includes year dummy variables. Standard errors in parentheses. Spending variable in entrant plan equation is indexed spending.
***1% statistical significance, **5% statistical significance, *10% statistical significance

Table 5: FFS Enrollment in Different Equilibria

	Employee Share of Premium		
	15%	50%	100%
Baseline	28.0%	28.0%	28.0%
Equilibrium	29.9	13.3	7.7
No spending effects	24.7	10.5	6.2
No traditional adverse selection	24.7	10.7	6.2
No extrapolation	29.4	13.2	7.7
Aging in place	19.0	12.5	9.7

Note: 15 percent is the current employee share of the premium.

Appendix Table 1: The Evolution of Spending

Variable	Probability of Use HMO	Probability of Use FFS	Ln(Spending) if use HMO	Ln(Spending) if use FFS
Intercept	2.660***	3.770***	5.742***	6.116***
	(0.019)	(0.041)	(0.009)	(0.017)
Visits lagged	0.046***	0.018***	---	---
	(0.001)	(0.002)		
Copay lagged	0.001***	0.007***	---	---
	(0.000)	(0.000)		
Demographics (omitted category is male 0-4)				
Male 5-19	-0.394***	-0.479***	-0.146***	-0.038**
	(0.018)	(0.040)	(0.009)	(0.014)
Male 20-34	-0.745***	-1.035***	-0.111***	0.078***
	(0.018)	(0.041)	(0.008)	(0.016)
Male 35-49	-0.609***	-0.651***	0.154***	0.343***
	(0.017)	(0.039)	(0.007)	(0.014)
Male 50-60	-0.482***	-0.514***	0.534***	0.644***
	(0.019)	(0.0340)	(0.007)	(0.014)
Male 61-65	-0.563***	-0.545***	0.686***	0.677***
	(0.025)	(0.041)	(0.010)	(0.014)
Female 0-4	-0.021	-0.013	-0.101***	-0.074***
	(0.023)	(0.053)	(0.009)	(0.018)
Female 5-19	-0.300***	-0.373***	-0.138***	-0.011
	(0.018)	(0.040)	(0.007)	(0.014)
Female 20-34	-0.272***	-0.524***	0.367***	0.359***
	(0.018)	(0.041)	(0.007)	(0.015)
Female 35-49	-0.304***	-0.353***	0.409***	0.533***
	(0.018)	(0.040)	(0.007)	(0.014)
Female 50-60	-0.334***	-0.345***	0.632***	0.677***
	(0.019)	(0.040)	(0.007)	(0.014)
Female 61-65	-0.858***	-0.500***	0.680***	0.619***
	(0.024)	(0.041)	(0.010)	(0.014)
Lagged spending (omitted category is the first decile – lowest positive spending)				
Negative spending	-0.385***	-0.933***	0.731***	1.170***
	(0.093)	(0.124)	(0.052)	(0.072)
Zero spending	-1.785***	-2.077***	0.098***	0.283***
	(0.008)	(0.015)	(0.005)	(0.009)
Second decile	0.348***	0.126***	0.178***	0.256***
	(0.011)	(0.020)	(0.005)	(0.001)
Third decile	0.601***	0.357***	0.353***	0.451***
	(0.012)	(0.021)	(0.005)	(0.010)
Fourth decile	0.835***	0.543***	0.544***	0.639***
	(0.013)	(0.023)	(0.005)	(0.010)

Appendix Table 1 (continued)

	Probability of Use		Ln(Spending) if use	
Variable	HMO	FFS	HMO	FFS
Fifth decile	1.021***	0.743***	0.754***	0.855***
	(0.015)	(0.025)	(0.052)	(0.009)
Sixth decile	1.225***	0.891***	0.970***	1.096***
	(0.018)	(0.027)	(0.005)	(0.009)
Seventh decile	1.329***	1.023***	1.198***	1.328***
	(0.020)	(0.030)	(0.005)	(0.009)
Eighth decile	1.377***	1.096***	1.442***	1.621***
	(0.023)	(0.033)	(0.006)	(0.009)
Ninth decile	1.216***	1.070***	1.672***	1.968***
	(0.025)	(0.037)	(0.006)	(0.009)
Tenth decile	0.857***	0.787***	2.016***	2.525***
(highest spending)	(0.027)	(0.039)	(0.006)	(0.008)
N	1,656,041	753,382	1,350,000	645,350
-2ln(L) / R^2	1,135,472	415,741	0.274	0.326

***1% statistical significance, **5% statistical significance, *10% statistical significance

Appendix Table 2: OLS Estimates of Other Relationships

Variable	Dependent Variable: ln(1+visits)	Dependent Variable: ln(1+copay)
Intercept	1.967***	1.600***
	(0.047)	(0.003)
ln(1+visits) lagged	0.469***	---
	(0.001)	
ln(1+visits) contemporaneous	---	0.329***
		(0.001)
FFS	0.066***	-0.238***
	(0.002)	(0.001)
Demographics (omitted category is Male 0-4)		
Male 5-19	-0.220***	---
	(0.004)	
Male 20-34	-0.200***	---
	(0.005)	
Male 35-49	-0.061***	---
	(0.004)	
Male 50-60	0.094***	---
	(0.004)	
Male 61-65	0.212***	---
	(0.005)	
Female 0-4	-0.062***	---
	(0.006)	
Female 5-19	-0.185***	---
	(0.004)	
Female 20-34	0.020***	---
	(0.005)	
Female 35-49	0.100***	---
	(0.004)	
Female 50-60	0.214***	---
	(0.004)	
Female 61-65	0.273***	---
	(0.005)	
Spending (omitted category is the first decile – lowest positive spending)		
Negative spending	---	0.825***
		(0.037)
Zero spending	---	-0.368**
		(0.163)
Second decile	---	0.435***
		(0.003)
Third decile	---	0.816***
		(0.003)
Fourth decile	---	1.134***
		(0.003)

Appendix Table 2 (continued)

	Dependent Variable	
Variable	ln(1+visits)	ln(1+copay)
Fifth decile	---	1.404***
		(0.003)
Sixth decile	---	1.627***
		(0.003)
Seventh decile	---	1.849***
		(0.003)
Eighth decile	---	2.080***
		(0.003)
Ninth decile	---	2.289***
		(0.004)
Tenth decile	---	2.441***
(highest spending)		(0.004)
N	1.55E+06	1.97E+06
R^2	0.294	0.668

***1% statistical significance, **5% statistical significance, *10% statistical significance