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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, enrollees' inertia in plan choice, leading plans with older enrollees to increase in relative cost over time. Using data from the Group Insurance Commission in Massachusetts, we show that adverse selection and aging in place are both quantitatively important. Either can materially impact equilibrium enrollments, especially when premiums to enrollees reflect these costs.

Policies to facilitate choice across insurance plans generate widespread support in the US, and in many countries around the world. The recent health reform in the United States, for example, creates health insurance exchanges to facilitate insurance choice among individuals and employees of small groups. The idea is popular in the Netherlands and Germany as well.

As is well known, the major issue inhibiting efficient sorting is health status-based plan selection. Selection 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 their 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, or indeed less, 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. This study assesses the factors influencing the movement of people across employer-sponsored health plans.

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 just 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 previous papers, including some by some current authors, have used data from this population (Altman et al., 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

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

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care in the future might move into plans where choice of providers is greater and/or out-of-pocket costs for care are lower. 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 individuals in that class Such selection is efficient, though it may be considered inequitable: those with higher morbidity, already afflicted, would pay more than the healthy for access to medical services.[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 but one factor influencing health plan choice. Transition costs may be important too. Such costs, for example, arise if insureds are concerned with maintaining continuity with their physicians, or indeed with 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 than is adverse selection. With no adverse retention, less generous plans lose enrollees whose expected costs rise, and gain enrollees whose expected costs fall. With adverse retention, both types of plans keep their high-cost members.

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 will depend on the way expected health spending increases with age. Generally, it has been observed, 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 will 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 estimate determinants of switching behavior and then incorporate these estimates into a simulation model to investigate long-term equilibrium outcomes. We find evidence that traditional adverse selection is a significant phenomenon, more important quantitatively than adverse retention. Adverse selection develops 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, i.e., 100% of the cost differential would reduce enrollment in the high-cost plan by two-thirds.

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 Section 3, we present estimated transition equations for movements between the two plans. In Section 4, 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.

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

1. 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. 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 for the services she uses.

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.

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, and that individuals know their risk *ex ante*.[5] Thus, higher risk individuals will disproportionately value the generous plan. However, the insured's premium for either plan is the same for all.

Consequently, 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).[6] 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."[7]

We will use the single index model as our benchmark, but some caveats should be stated. We have already left the world of first-

[3] Other factors that may affect plan choice might not affect efficiency, depending on the importance of those factors relative to price. For example, if personal preferences drive plan choice much more than does price, 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 need not generate inefficiency. 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.

[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.

[6] As Bundorf et al. (2008) point out, this assumes that the value of more generous coverage increases with risk more than the cost of more generous coverage, and that only risk matters for choice.

[7] Pauly et al. (2007) argue that movement out of the fee-for-service plan may reflect consumers learning that the product is worse for them, not just adverse selection.

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).

1.1. Backward-looking selection

It is possible that people value the different plans not as the model suggests on a fully rational basis, but using heuristics. Salience based on past experience is a natural heuristic. An individual who has high costs because she contracts diabetes might choose the generous plan because she knows she 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 her expected future costs will be far lower.[8] 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.[9] 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.

1.2. Adverse retention

In the traditional choice model, the costs of switching from one plan to another – both tangible and psychological – are assumed away. We relax this assumption, and allow switching costs to differ. It is plausible that such costs increase with one's level of spending. Personal preference will also affect switching costs.

Past spending could correlate positively with switching costs for multiple reasons. First, individuals receiving treatment 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 her, all else equal, her personal doctors are much better than the average. (Remember, also, that the individual played a role in selecting her 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 change any choices. Perhaps high medical costs, a signal of the past treatment of many or serious problems, reinforce this bias.

This positive correlation produces 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 than healthier people to remain in the generous plan. 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 such people more likely to remain in the moderate plan.

1.3. Aging in place

If individuals like their current plan a good deal, or if they do not but moving costs are high, 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 landed. They would then age in place, which becomes an ever increasing burden on a plan until old members retire or die. Fig. 1 graphs average costs in our data by age and sex. There is a clear non-linear pattern: once past 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 and simply aged one year, the average cost differential between the FFS plan and the HMO would rise by 3.5% over the next year.

Even if individuals do not switch, they do not stay fixed; some age out of the group. Once aging out becomes sufficient, the initially more expensive plan becomes the cheaper plan. That is, assuming no other changes, ultimately 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 no one switched plans, and all plans survived the strain of rising premiums.

1.4. 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.[10] Spending would offer a crude way to measure exposure to unsatisfactory encounters. A more powerful measure, which we will use, looks at billing errors as the stimulus for being fed up. Note that the fed-up phenomenon would exert an effect that is precisely the opposite to the direction of the adverse retention model.

2. Empirical framework

Our empirical work examines how monetary costs and health spending affect plan choices. It differentiates among adverse

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

[9] 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).

[10] Note if individuals have some leeway in timing healthcare services, there will be cases where if a person is fed up early in a prescribed period, she will then refrain from receiving further services from that plan. An endogenous feedback effect from fed-upness to low health-care spending within that plan and period will lead to an eventual switch.

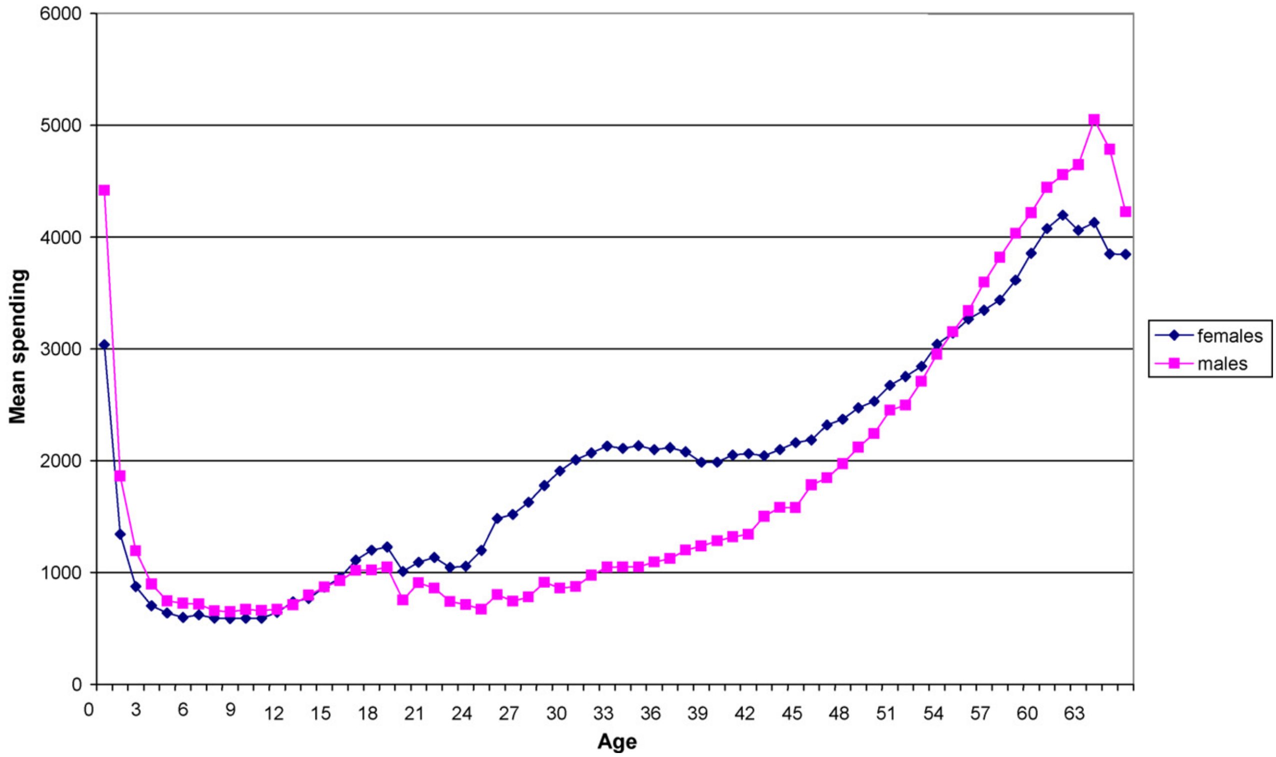

Fig. 1. Average spending by age and sex. *Notes*: Data are from the Group Insurance Commission. Spending is adjusted for cross-year means.

selection, adverse retention, and aging in place. Following our theoretical discussion, it is important to divide the population by initial plan enrollment. We sort people into two initial locations: those in the FFS plan and those in the HMO.

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

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

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 implies that $\alpha_{\hat{S}} > 0$. If people form their expectation of future spending based on past spending (backward-looking selection) or if high spending in the past causes people to remain in their current plan (adverse retention), then we would expect $\alpha_S > 0$. One might alternatively model adverse retention as depending on the number of visits in the past – more visits makes one more attracted to current providers – 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. Lower copays, all else equal, means cheaper health insurance, so we expect $\alpha_C < 0$. The vector X includes demographic factors that might influence mobility, including age and sex.

There is an analogous equation, though with quite different implications, for the value of the FFS plan for people currently enrolled in the HMO:

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

For this group, adverse selection would imply that $\beta_{\hat{S}} > 0$ or $\beta_S > 0$, depending on whether selection is based on expected future spending or past spending. In contrast, adverse retention would imply just the opposite: $\beta_S < 0$, or high spending people are less likely to switch plans. If people respond instead to increased numbers of visits in the past, the coefficient β_V will be positive given adverse selection, or negative given adverse retention.

Estimating how premiums affect 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 the gap between the premiums for the two plans varied greatly over time (as it did in the sample of 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; Strombom et al., 2002).

3. Data

Our data includes all medical claims from fiscal years 1994 to 2004 for all Massachusetts state employees and their families covered by the state's health insurance system, which is run by the Group Insurance Commission (GIC), and for the small percentage of local public employees also covered by the GIC. 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, increasing 85 cents for each dollar of cost. The heavy subsidization of marginal premium costs by the GIC could possibly approximate some type of second-best cross-subsidy risk adjustment (see Selden, 1999), but if true that would be fortuitous. There is nothing explicit—each plan stands nominally on its own. It would be miraculous if 85% were the right sharing percent to get close to the optimal cross-subsidy.[11]

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. All of our regressions include year dummy variables so that price changes are not an issue.

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, and visits 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 a family in each demographic bin. These variables change as family composition and ages change.

For families who switch from one plan to another 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 family not changed plans. This produces the index problem of translating one plan's spending into what the equivalent would have been in the other. The data appendix explains how we computed this indexed spending variable. Briefly, we estimate a common price difference between managed care and the FFS insurer, and then use this differential to adjust spending across plans.[12] The average discount in the HMOs is 27%.

Insurance claims data often have records with negative charges due to subsequent revisions in original billed amounts. Aggregated at the yearly level, total spending includes some negative values, presumably due to billing mistakes that have not yet been fixed, or past year mistakes now being fixed.[13] We correct billing mistakes as we are able (see data appendix), but cannot offset all of them.[14]

Table 1
Summary statistics for plan mobility data.

Measure	FFS plan (32%)		HMOs (68%)	
	Mean	Standard deviation	Mean	Standard deviation
Age (years)	41.6	19.0	31.7	18.0
Spending (dollars)	$2974	$10,945	$1548	$6647
Copay (dollars)	$141	$255	$102	$185
Visits (number)	7.2	11.2	5.7	8.5
Percent positive spending	86%		81%	
Entrant rate	12%		11%	
Exit rate	17%		10%	
Switching 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%	

Notes: Data are for the Group Insurance Commission and are averages for all years 1994–2004. Entrants and exits refer to the GIC pool as a whole, while switching refers to movement from an HMO to the FFS plan, or vice versa.

All possible observations on families with non-elderly individuals are employed in our switching equations. Thus, for our equations estimating the probability of moving from one plan in year $t-1$ to another in year t, we include all people who were in the GIC in both years $t-1$ and t and for whom demographics are known in each year.

Eqs. (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, would a quadratic in spending.

Fig. 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 that individuals face between the FFS plan and the HMOs.[15] Participation in the FFS drops in the early years from about 40% to 25%, with a modest rebound starting in 2001. The reduction in FFS enrollment accompanied a rise in the premium differential between the two plans, as theory would predict. The flattening of the loss in FFS percentage coincided 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.

Fig. 3 shows 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 pattern well known in health care. The FFS distribution has fewer people with no spending, and a spending distribution shifted to the right of the HMO distribution.

[11] That said, the 85% subsidy may be closer to optimal than no subsidy, which is common in many firms.

[12] This assumes something like the higher spending we see for what is categorized as the same services across plans is entirely due to price differences, as has been argued to be the case (Altman et al., 2003; Cutler et al., 2000). If this assumption is exactly right, it implies that there is no difference in the quantity of services received across plans, only the prices paid for them. One interpretation of this is pure rent—a transfer from patients to doctors. A second interpretation is that the higher prices lead to greater access to physicians with higher demand. This might explain why spending risk measures have relatively little effect on demand; in essence, spending risk is not the key variable. In the absence of data on which physicians a particular patient sees, we do not explore this in great detail.

[13] 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.

[14] For yearly family spending we are left with .06% observations that are negative. All results are similar if these observations are omitted.

[15] The differential is calculated as average costs in each plan after the subsidy and a markup for administration charges.

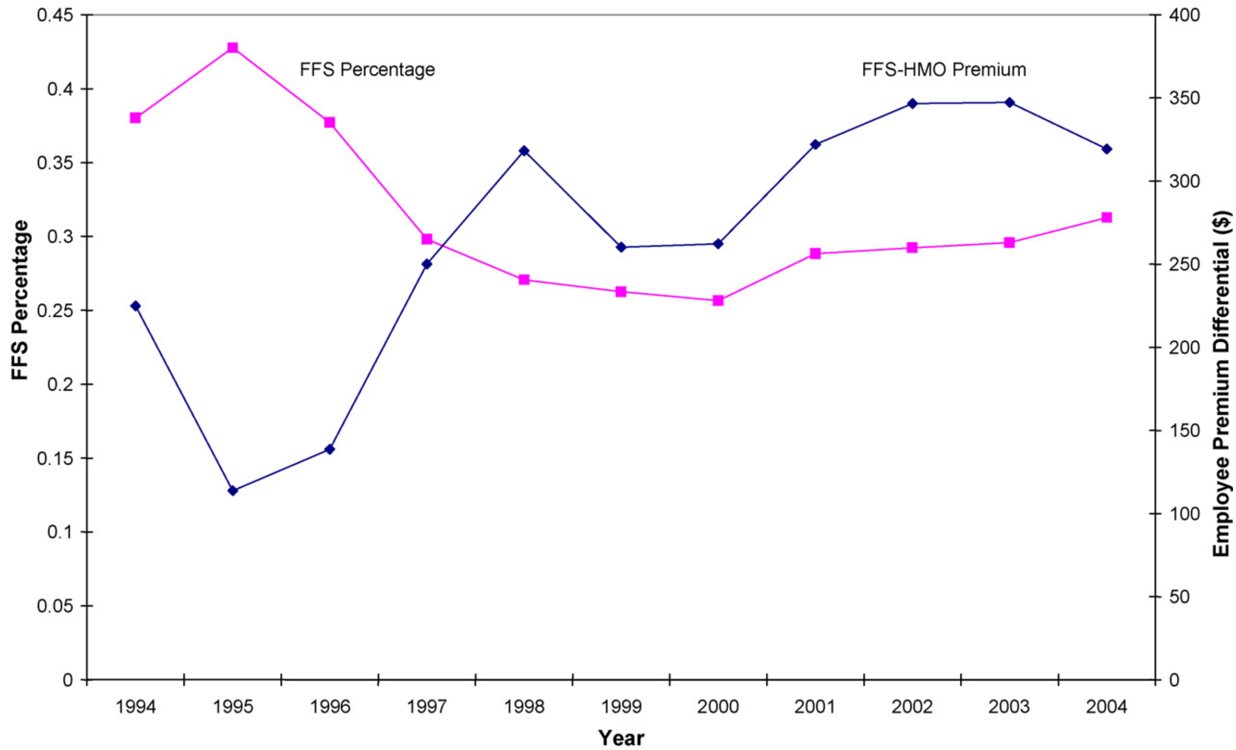

Fig. 2. FFS percentage enrollment and the difference in premiums. *Notes*: The FFS plan percentage of all members is on the left scale. The difference between average FFS and HMO spending, after the 85% premium subsidization and a 10% loading factor, is on the right scale.

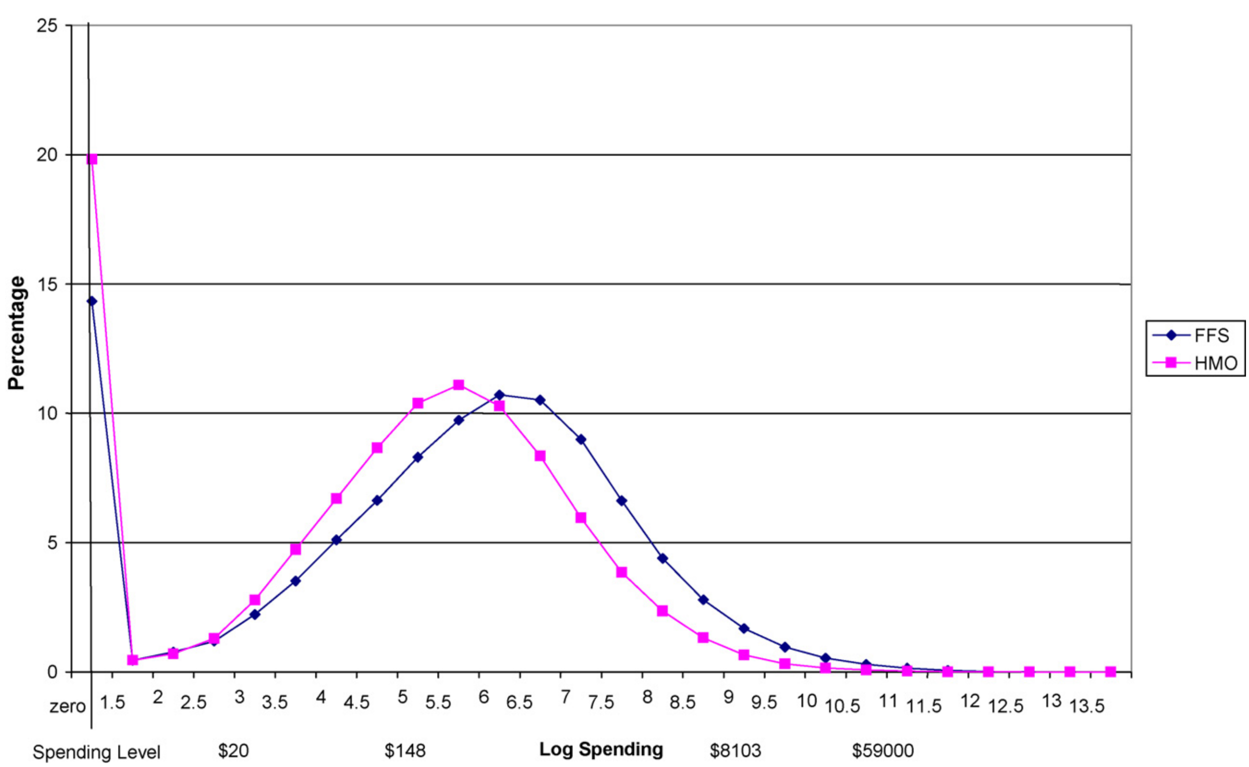

Fig. 3. Log spending, by plan. *Notes*: Spending is adjusted for cross-year means. For reference, several representative numbers in dollars are reported.

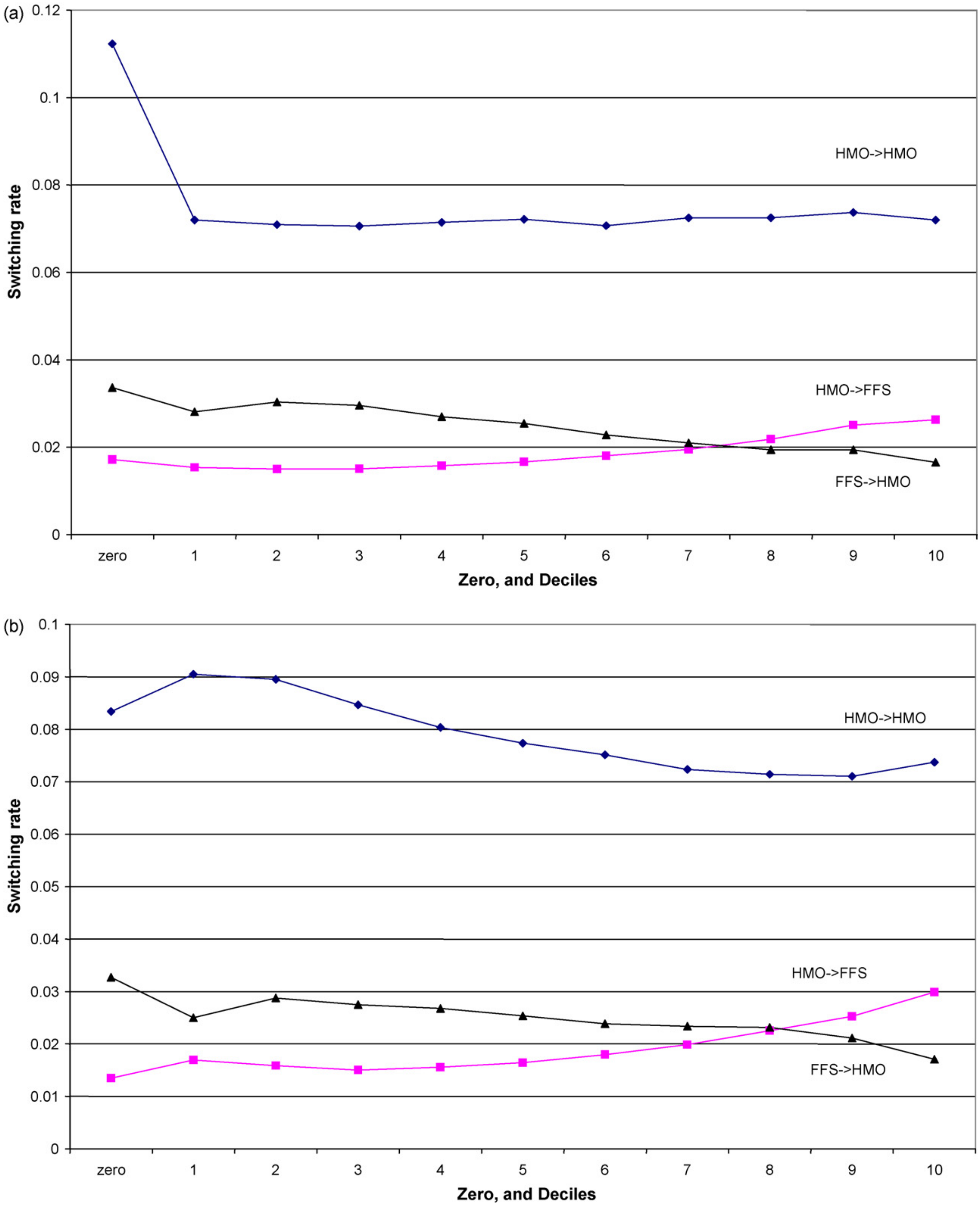

Fig. 4. (a) Switching rates by spending deciles in base year. *Notes*: The chart shows plan switching rates among zero spenders and each decile of spending in the base year plan. For example, the HMO → FFS line shows the share of people who leave the HMO in year $t-1$ for the FFS plan in year t within each bucket of spending in the HMO in year $t-1$. (b) Switching rates by spending deciles in subsequent year. *Notes*: The chart shows switching rates among zero and positive decile post-switching spending distributions. For example, the HMO → FFS line shows where in the distribution of HMO spending in year t the people who left the HMO for the FFS plan between years $t-1$ and t would have been had they remained in the HMO. For people who switch plans, spending is converted to the initial plan using the indexing methodology described in Appendix A. (c) Arrival rates by spending decile in subsequent year. *Notes*: The chart shows the share of switchers in spending deciles of the post-switch plan. For example, the HMO → FFS line shows the share of people in each decile of the FFS plan in year t who moved from the HMO to the FFS plan between years $t-1$ and t.

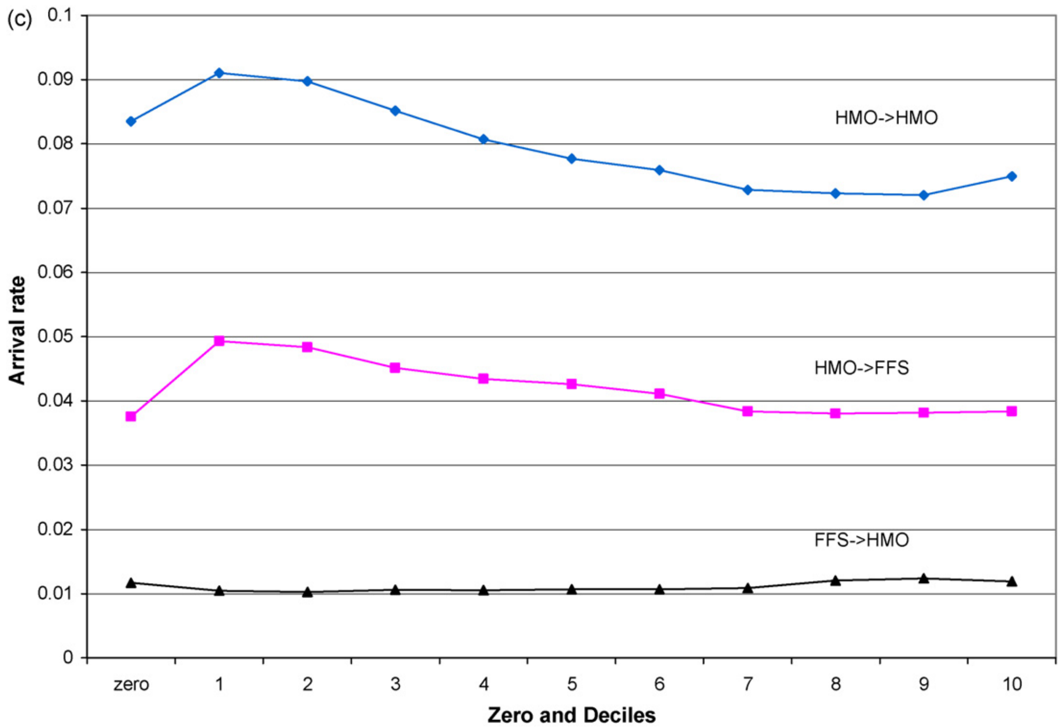

Fig. 4. (*Continued*).

Table 1 presents some basic summary statistics of the dataset at the individual level, broken down by the two plans. Over the entire time period, the FFS plan averages about one-third of the total GIC membership. It has a much higher percentage of persons at older ages, as adverse selection would predict.[16] The percentage of those 50 and older is 45% for the FFS versus 18% for the HMO. The difference in average age for the two plans is ten years. Computing the ratio of very young children, ages 0–4, to women of ages 20–34, 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 pattern is not surprising given the much younger age composition in the HMO plans. Presumably, there is significant but not extreme adverse selection towards the FFS plan for women expecting babies.

Both number of visits and total copays are lower for the HMO. "Exits" refer to insureds leaving the GIC entirely. Similarly "entrants" refer to new members of the GIC system. The exit rate is higher in the FFS plan, reflecting the plan's older population. Among entrants into the FFS plan, 35% are age 50 and higher (not shown.) The corresponding number for the HMO is a mere 10%.

4. Selection results

In this section, we estimate enrollment Eqs. (1) and (2). As a first broad overview, Fig. 4(a)–(c) shows mobility rates between plans by spending level. It also breaks out movement across the various HMOs in the system. In Fig. 4(a) we examine switches from the point of view of the plan the family potentially left. Each data point shows the share of people in that beginning plan's particular spending bucket who left that plan at the end of the year. The first observation is for people who use no services during the year; the positive spenders are then divided into ten deciles from lowest to highest.[17] As an example, for insureds in the third decile of spending in the HMO plan, approximately 1.5% will then switch to the FFS plan. Among those in the ninth decile of spending in the FFS plan, approximately 2% will then leave for the HMO plan.

There is clear evidence of adverse selection. For people initially in an HMO, transitions from the HMO to the FFS rise monotonically beyond the second decile. The reverse is true for people initially in the FFS plan: switching rates decrease with spending.

Fig. 4(b) shows where plan switchers would have ended up in the distribution of their initial plan spending had they not left. We take actual spending for those who stayed and index the spending of those who switched plans to bring them back to what their spending would have been in their initial plan. We create deciles out of this hybrid group of spending and then count the share of switchers in the previous year within these deciles.

In this chart, there is decreased mobility from one HMO to another at higher deciles, in accord with adverse retention. Other evidence supports forward-looking 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 Fig. 4(c) looks at how expensive plan switchers are relative to people already in the plan they join. It shows the arrival rate—the share of people in each spending bucket who came from the other plan in the previous year. As an example, in the eighth decile of spending in the HMO, approximately 1.2% of its members will be people who switched last year from the FFS. And the sixth decile of spending of the FFS has about 4% coming from the HMO.

Arrival rates also produce a pattern consistent with the single index model. Subsequent spending among people who leave the HMO tends to be at the lower end of the FFS distribution. Arrival

[16] HMOs were a less significant phenomenon in early years, suggesting that this may also be due to aging in place, individuals being reluctant to shift plans.

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

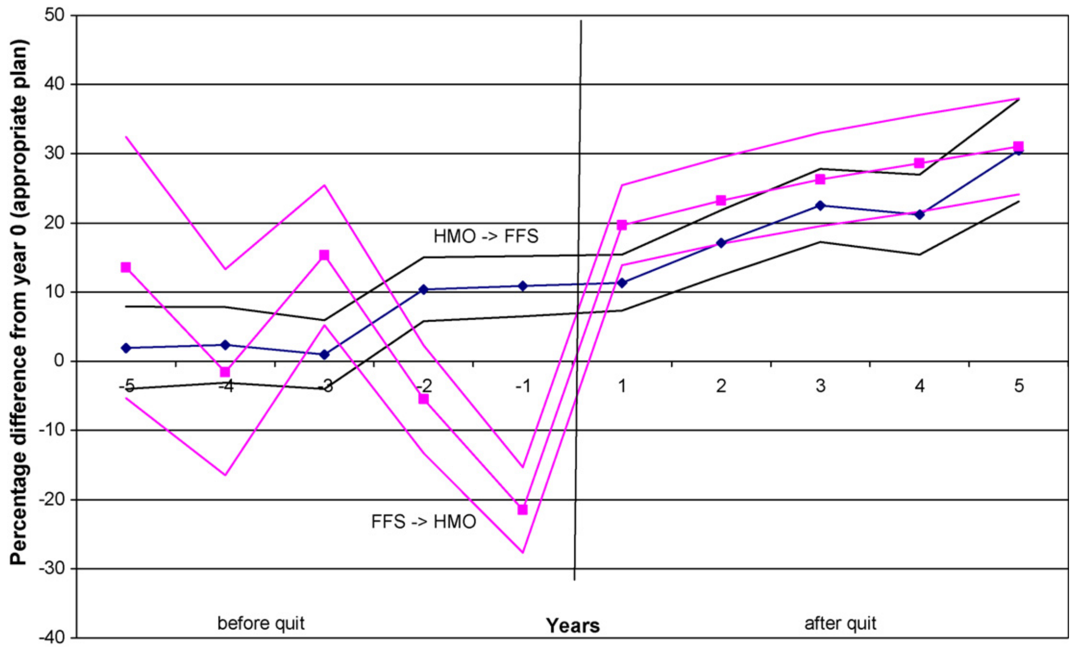

Fig. 5. Family spending before/after switch (with 95% confidence bands). *Notes*: The figure is based on a linear regression of family ln(spending), with year, demography, and current plan as dummy variables. The horizontal scale is time, where 0 is the year of the switch. Thus, −1 represents the year before the switch. The omitted category is families who did not move during any of these periods. The line with squares (diamonds) graphs dummy coefficients for number of years before/after switch from the FFS to the HMO (from the HMO to the FFS). Solid lines are 95% confidence bands around these dummy coefficients.

rates into the HMO from the FFS plan are relatively flat by spending level, with a very small uptick at the highest deciles.

While the patterns in Fig. 4 are consistent with adverse selection, we note that the magnitude of the effect and its consequence for expenditures are moderate. Only 2.5% of those in the top decile of the HMO plan move to the FFS plan, and they account for but 4% of the FFS enrollees. Even if all of these enrollees ended up in the top decile of the FFS plan (they do not—see Fig. 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.

Although not our primary focus, Fig. 4(a)–(c) shows the transition rates from one HMO to another as well. There is mild evidence of adverse retention in these data. People who move from one HMO to another spend less in the next year than people in the plan they left, and than people in the plan they join.

Fig. 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 (Maciejewski et al., 2004). 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 estimate regression models relating spending for each family in each year to dummies for year before a switch, two years before a switch, year after a switch, etc. Year −1 is the year before the change and year 1 is the first year after the change, so there is no year 0. A separate set of dummies was created for a switch from FFS and for a switch from HMO. We control for year and plan dummy variables, and for basic demographics (age and sex).

Fig. 5 shows relative spending in the five years before and after a plan transition, along with 95% confidence bands.[18] While there are possible attrition issues (an observation for a person 3 years before a switch 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 varies considerably in the 3–5 years prior to the switch. It then drops precipitously in the two years just prior to the move. Indeed, in the immediate prior-year spending is 20% below that of the switch year. 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. After the move, switchers spend 20–30% more than those always in the HMO. Among those who move from the HMO to the FFS plan, spending is high in the two years prior to the move, about 10% higher than for non-movers.[19] Their spending remains higher after the switch, even relative to those in the FFS plan the entire time.

For the switch from the FFS to the HMO plan, Fig. 5 fits the simplest single index model story, for both before and after the switch. In years just before the switch movers are below average in spending in the FFS plan, and after the switch are in the upper part of the HMO distribution. For a switch from the HMO to the FFS, we see that before the switch movers are high in the HMO distribution, also consistent, but we have the anomaly that they are then also high in the subsequent FFS distribution. This latter result does not fit with a tight uni-modal distribution of shocks to spending, leading to movers leaving and landing close to the "border" at the risk cutoff point between the two plans.

One possible explanation for this asymmetry is to invoke adverse retention and status quo bias. For FFS members with lower morbidity there is less demand for medical services so adverse retention is a smaller consideration. For HMO members who are experiencing higher morbidity there may need to be a larger jump to overcome their current relationship with doctors, concerns with

[18] The omitted category is families who do not move during all these periods.

[19] We do not see those a year from moving decreasing their spending in anticipation of more generous care in the destination FFS plan, as found in Tchernis et al. (2006).

Table 2
Logistic regressions for plan switching from HMO to FFS.

Variable	Demographics		Future spending		Past spending		All	
	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk
Intercept	−4.096*** (0.042)		−4.007*** (0.045)		−4.075*** (0.044)		−4.263*** (0.056)	
Visits	0.001 (0.001)	1.01	−0.009*** (0.001)	0.87	−0.008*** (0.001)	0.88	−0.003*** (0.001)	0.96
Copay	0.000*** (0.000)	1.04	0.000*** (0.000)	1.10	0.000*** (0.000)	1.12	−0.000 (0.000)	0.98
Any negative Claims	−0.203*** (0.020)	0.82	−0.252*** (0.020)	0.78	−0.209*** (0.021)	0.82	−0.211*** (0.021)	0.81
Demographics								
Male 0–4	−0.110*** (0.035)	0.90	–		–		−0.156*** (0.036)	0.86
Male 5–19	−0.174*** (0.018)	0.84	–		–		−0.167*** (0.018)	0.85
Male 20–34	−0.133*** (0.029)	0.88	–		–		−0.148*** (0.029)	0.86
Male 35–49	−0.019 (0.027)	0.98	–		–		−0.027 (0.027)	0.97
Male 50–60	0.094*** (0.025)	1.10	–		–		0.070*** (0.026)	1.07
Male 61–65	0.589*** (0.029)	1.77	–		–		0.555*** (0.030)	1.71
Female 0–4	−0.144*** (0.036)	0.87	–		–		−0.183*** (0.037)	0.84
Female 5–19	−0.161*** (0.018)	0.85	–		–		−0.154*** (0.018)	0.86
Female 20–34	−0.006 (0.028)	0.99	–		–		−0.010 (0.027)	0.99
Female 35–49	0.217*** (0.028)	1.24	–		–		0.215*** (0.028)	1.23
Female 50–60	0.464*** (0.028)	1.57	–		–		0.450*** (0.029)	1.55
Female 61–65	1.224*** (0.032)	3.23	–		–		1.211*** (0.032)	3.19
Indexed future spending (omitted category is the first decile—lowest positive spending)								
Negative spending	–		−1.508** (0.712)	0.23	–		−1.569** (0.713)	0.21
Zero spending	–		−0.195*** (0.043)	0.83	–		−0.451*** (0.045)	0.64
Second decile	–		−0.023 (0.042)	0.98	–		0.009 (0.042)	1.01
Third decile	–		0.023 (0.041)	1.02	–		0.068 (0.043)	1.07
Fourth decile	–		0.082** (0.041)	1.08	–		0.136*** (0.043)	1.14
Fifth decile	–		0.121*** (0.041)	1.13	–		0.175*** (0.044)	1.19
Sixth decile	–		0.160*** (0.041)	1.17	–		0.214*** (0.044)	1.23
Seventh decile	–		0.275*** (0.041)	1.31	–		0.309*** (0.044)	1.35
Eighth decile	–		0.344*** (0.041)	1.40	–		0.375*** (0.045)	1.44
Ninth decile	–		0.523*** (0.041)	1.66	–		0.574*** (0.044)	1.75
Tenth decile (highest spending)	–		0.588*** (0.042)	1.77	–		0.552*** (0.045)	1.71
Past spending (omitted category is the first decile—lowest positive spending)								
Negative spending	–		–		−0.067 (0.387)	0.94	−0.274 (0.396)	0.76
Zero spending	–		–		0.291*** (0.035)	1.33	0.412*** (0.038)	1.49
Second decile	–		–		−0.160*** (0.038)	0.86	−0.232*** (0.039)	0.80
Third decile	–		–		−0.039 (0.038)	0.96	−0.185*** (0.039)	0.83
Fourth decile	–		–		−0.015 (0.037)	0.99	−0.205*** (0.040)	0.82
Fifth decile	–		–		−0.012 (0.039)	0.99	−0.259*** (0.042)	0.78
Sixth decile	–		–		0.075* (0.040)	1.08	−0.210*** (0.043)	0.81

Table 2 (*Continued*)

Variable	Demographics		Future spending		Past spending		All	
	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk
Seventh decile	–		–		0.130*** (0.040)	1.14	−0.168*** (0.043)	0.85
Eighth decile	–		–		0.159*** (0.043)	1.17	−0.205*** (0.046)	0.82
Ninth decile	–		–		0.201*** (0.044)	1.22	−0.133*** (0.048)	0.88
Tenth decile (highest spending)	–		–		0.428*** (0.051)	1.52	−0.010 (0.056)	0.99
N	704,857		705,619		706,812		704,857	
$-2\log L$	139,626		143,281		143,680		138,747	

Notes: Data are for 1994–2004. Equations are estimated at the family-year level. Year dummy variables are included. Indexed future spending is actual future spending for stayers, and for switchers the same adjusted to be comparable to spending as if they had stayed, see text and data appendix. Demographic variables are the total number of people in that age–sex group in the family. Huber–White standard errors corrected for within family correlation across time are in parentheses.

*** 1% statistical significance.

** 5% statistical significance.

* 10% statistical significance.

disruption in treatment, etc. Adverse retention interacts with the direction of medical demand change leading to an asymmetry in moving costs, which then would predict this empirical pattern.

We now turn to the transition equations proper. Table 2 reports logistic equations for movement from the HMO to the FFS plan. First we have demographic variables along with visits and copays in the year prior to the switch. Note again these inter-plan switch equations are estimated at the family level since it is the family as a whole that moves. For demographic dummy variables this means we do not have an omitted category. For example, a household with newborn male twins would have their male 0–4 variable coded as 2, etc. For spending variables we include a dummy for negative total spending during the year and another dummy if there is at least one negative charge (offset or not) 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.[20] The table reports the logit coefficients, Huber–White standard errors corrected for family level heteroscedasticity associated with a family being in the data for multiple years, and the relative risk of switching for the associated variable.

The first column indicates that demography strongly affects plan mobility. Families with older members – presumably at higher risk and selecting adversely to the plan – 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 at least 75% more likely to switch plans than younger adult males. Thus, selection overcomes the presumed greater flexibility of younger men.

The second column includes (indexed) subsequent year spending. Including future spending represents a specification assuming fully—rational, forward-looking behavior. There are dummies for zero spending and each positive decile of spending (the omitted dummy is spending in the first decile).

The results on future spending confirm Fig. 4(b): people in upper deciles are far more likely to switch plans than those in the lowest deciles. The effect is monotonic in spending and large: those at the top of the spending distribution are nearly 80% more likely to switch plans than those at the bottom of the distribution. Having additional visits, by itself, has little effect on plan mobility, indeed its effect changes signs across different specifications.

[20] 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.

Further, omitting visits does not affect the coefficients on future spending (not shown). The coefficient on out-of-pocket payments is statistically significant but small, and also switches signs across specifications. Again, excluding copayments does not greatly affect the coefficients on spending. People with negative claims during the past year are much less likely to switch to the FFS, evidence against the idea that people fed up with errors switch plans.

The third column posits backward-looking behavior. It predicts mobility on the basis of spending in the year prior to a potential switch. Zero past spending has a substantial positive effect on plan switches (33% higher relative risk), as does very high past spending (52% higher relative risk at the 10th decile).

In column 4 we estimate all these variables simultaneously. The major change with all covariates included is that 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. Of course demographics in many ways can be seen as another forecast variable, one that only changes slowly. Advancing age can increase both the frequency and severity of morbid conditions. That both demographics and future spending matter may just be telling us something about the forecast method people use to project medical spending.

Table 3 repeats the analysis in Table 2, considering movement from the FFS plan to the HMO. The number of visits in the previous year again has alternating signs, similar to that found in Table 2. Larger copays slightly lower the rate of switching plans. 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 for an HMO than are younger people. The difference between prime age and older individuals is 50% and higher. 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.

Table 3
Logistic regressions for plan switching from FFS to HMO.

Variable	Demographics		Future spending		Past spending		All	
	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk
Intercept	−3.410***		−3.759***		−3.603***		−3.380***	
	(0.046)		(0.055)		(0.045)		(0.069)	
Visits	−0.005***	0.92	0.001	1.02	0.006***	1.10	−0.000	0.99
	(0.001)		(0.001)		(0.001)		(0.001)	
Copay	−0.000***	0.92	−0.001***	0.82	−0.000***	0.87	−0.000**	0.95
	(0.000)		(0.000)		(0.000)		(0.000)	
Any negative Claims	0.101***	1.10	0.096***	1.10	0.182***	1.19	0.365	1.43
	(0.030)		(0.029)		(0.030)		(0.431)	
Demographics								
Male 0–4	0.273***	1.30	–		–		0.302***	1.34
	(0.035)						(0.035)	
Male 5–19	0.139***	1.15	–		–		0.149***	1.16
	(0.021)						(0.021)	
Male 20–34	0.208***	1.22	–		–		0.215***	1.23
	(0.029)						(0.029)	
Male 35–49	−0.121***	0.89	–		–		−0.114***	0.89
	(0.028)						(0.029)	
Male 50–60	−0.376***	0.69	–		–		−0.364***	0.70
	(0.031)						(0.031)	
Male 61–65	−0.755***	0.48	–		–		−0.732***	0.49
	(0.052)						(0.052)	
Female 0–4	0.214***	1.23	–		–		0.239***	1.26
	(0.037)						(0.038)	
Female 5–19	0.128***	1.13	–		–		0.135***	1.14
	(0.022)						(0.022)	
Female 20–34	0.286***	1.32	–		–		0.287***	1.32
	(0.024)						(0.025)	
Female 35–49	−0.087***	0.92	–		–		−0.083***	0.92
	(0.025)						(0.026)	
Female 50–60	−0.496***	0.61	–		–		−0.491***	0.62
	(0.030)						(0.031)	
Female 61–65	−1.578***	0.21	–		–		−1.553***	0.22
	(0.059)						(0.059)	
Indexed future spending (omitted category is the first decile—lowest positive spending)								
Negative spending	–		0.458	1.56	–		0.365	1.43
			(0.420)				(0.431)	
Zero spending	–		0.095*	1.10	–		0.000	1.00
			(0.051)				(0.056)	
Second decile	–		−0.038	0.96	–		0.026	1.03
			(0.057)				(0.058)	
Third decile	–		0.081	1.08	–		0.198***	1.21
			(0.056)				(0.057)	
Fourth decile	–		0.014	1.01	–		0.170***	1.18
			(0.056)				(0.059)	
Fifth decile	–		0.100*	1.10	–		0.281***	1.31
			(0.056)				(0.059)	
Sixth decile	–		0.112**	1.12	–		0.308***	1.35
			(0.056)				(0.060)	
Seventh decile	–		0.119**	1.12	–		0.315***	1.36
			(0.056)				(0.060)	
Eighth decile	–		0.073	1.07	–		0.267***	1.30
			(0.058)				(0.062)	
Ninth decile	–		0.043	1.04	–		0.191***	1.20
			(0.059)				(0.063)	
Tenth decile (highest spending)	–		−0.131**	0.88	–		0.066	1.07
			(0.060)				(0.064)	
Past spending (omitted category is the first decile—lowest positive spending)								
Negative spending	–		–		−0.462	0.64	−0.560	0.58
					(0.417)		(0.424)	
Zero spending	–		–		−0.063	0.94	−0.099**	0.91
					(0.046)		(0.049)	
Second decile	–		–		−0.192***	0.83	−0.314***	0.74
					(0.057)		(0.060)	
Third decile	–		–		−0.065	0.94	−0.188***	0.83
					(0.055)		(0.059)	
Fourth decile	–		–		−0.210***	0.81	−0.353***	0.71
					(0.053)		(0.058)	
Fifth decile	–		–		−0.287***	0.75	−0.414***	0.67
					(0.056)		(0.062)	
Sixth decile	–		–		−0.316***	0.73	−0.463***	0.63
					(0.056)		(0.062)	

Table 3 (*Continued*)

Variable	Demographics		Future spending		Past spending		All	
	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk	Coefficient	Relative risk
Seventh decile	–		–		−0.343*** (0.054)	0.71	−0.541*** (0.060)	0.59
Eighth decile	–		–		−0.418*** (0.058)	0.66	−0.556*** (0.065)	0.58
Ninth decile	–		–		−0.496*** (0.061)	0.61	−0.648*** (0.067)	0.53
Tenth decile (highest spending)	–		–		−0.656*** (0.069)	0.52	−0.731*** (0.073)	0.49
N	371,874		371,906		372,592		371,874	
$-2\log L$	75,009		78,502		78,434		74,803	

Notes: Data are for 1994–2004. Equations are estimated at the family-year level. Year dummy variables are included. Indexed future spending is actual future spending for stayers, and for switchers the same adjusted to be comparable to spending as if they had stayed, see text and data appendix. Demographic variables are the total number of people in that age–sex group in the family. Huber–White standard errors corrected for within family correlation across time are in parentheses.

*** 1% statistical significance.

** 5% statistical significance.

* 10% statistical significance.

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 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 family entrants. Demographics remain important: older entrants are much less likely to sign up for the HMO than the FFS plan. The future indexed 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.

5. 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. Forecasts of future spending and other variables must also be specified. Because the full set of equations is a complicated non-linear system, there is no closed-form solution. A simulation model, however, can provide 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 same 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 Table A1 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. Adult women spend more than men in all age groups but the highest. Higher prior-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 Table A2 shows a sizable coefficient on lagged visits in predicting the current number of visits, indicating a fair amount of persistence. Older people have more visits, as do women of child-bearing age. People in the HMO have on average 7% 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 linear 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 the number of visits and total spending during the year. Surprisingly HMO copays are 24% higher than for the FFS plan, controlling for these other variables.

To simulate the equilibrium, we draw a random sample of families from our dataset from the chosen base year of 2003.[21] Using this base year population, we simulate subsequent individual spending, copayments, and number of visits, adding to the fitted equations a random variate from a normal distribution whose variance equals the one estimated from the appropriate equation. We then sum the results for our sample of families.

The individual predictions and estimated premiums then feed into the transition equations. Where we have probabilistic equations (for example, switching plans), we first calculate the family's logistic cutoff point, and then draw a standard uniform random variable to determine the outcome. For all of the assumptions about the structure of our model that we have tried, this process

[21] Year 2003 was chosen because it is near the end of the sample.

Table 4
Plan choice among new entrants and people exiting.

Variable	New entrants (FFS = 1; HMO = 0)		Leaving GIC (exit = 1; remain = 0)	
	Coefficient	Relative risk	Coefficient	Relative risk
Intercept	−0.774*** (0.043)		−1.195*** (0.018)	
Visits	–		−0.009*** (0.001)	0.87
Copay	–		−0.001*** (0.000)	0.80
FFS	–		0.258*** (0.008)	1.26
Male 0–4	−0.028 (0.034)	0.98	0.213*** (0.014)	1.21
Male 5–19	−0.218*** (0.021)	0.85	0.050*** (0.009)	1.05
Male 20–34	−0.367*** (0.025)	0.75	−0.441*** (0.012)	0.67
Male 35–49	−0.072*** (0.026)	0.95	−0.757*** (0.012)	0.49
Male 50–60	0.324*** (0.028)	1.26	−0.945*** (0.015)	0.41
Male 61–65	0.955*** (0.046)	1.84	−0.231*** (0.013)	0.81
Female 0–4	−0.053 (0.035)	0.96	0.182*** (0.014)	1.18
Female 5–19	−0.211*** (0.021)	0.85	0.068*** (0.009)	1.06
Female 20–34	−0.467*** (0.025)	0.69	−0.159*** (0.011)	0.86
Female 35–49	0.064** (0.026)	1.05	−0.623*** (0.012)	0.56
Female 50–60	0.814*** (0.027)	1.70	−1.043*** (0.014)	0.37
Female 61–65	1.649*** (0.040)	2.49	0.282*** (0.011)	1.29
Indexed spending for entrant equation, actual spending for exit equation (omitted category is the first decile—lowest positive spending)				
Negative spending	–		0.404*** (0.095)	1.43
Zero spending	−0.318*** (0.032)	0.78	−0.281*** (0.013)	0.77
Second decile	−0.154*** (0.039)	0.89	−0.126*** (0.013)	0.89
Third decile	−0.294*** (0.040)	0.80	−0.520*** (0.014)	0.62
Fourth decile	−0.335*** (0.040)	0.77	−0.771*** (0.016)	0.49
Fifth decile	−0.318*** (0.040)	0.78	−0.902*** (0.018)	0.43
Sixth decile	−0.236*** (0.040)	0.84	−1.043*** (0.020)	0.37
Seventh decile	−0.284*** (0.041)	0.80	−1.080*** (0.022)	0.36
Eighth decile	−0.188*** (0.041)	0.87	−1.093*** (0.024)	0.36
Ninth decile	−0.136*** (0.041)	0.90	−1.010*** (0.026)	0.39
Tenth decile (highest spending)	−0.001 (0.042)	1.00	−0.582*** (0.027)	0.58
N	90,844		1,099,728	
$-2 \log L$	91,593		591,985	

Notes: Data are for 199–2004. Equations are estimated at the family level for the entrant equation and the family-year level for the exit equation. Year dummy variables are included. The spending variable in the entrant plan equation is indexed spending. Demographic variables are the total number of people in that age–sex group in the family. Huber–White standard errors corrected for within family correlation across time (in the exit equation) are in parentheses.
*** 1% statistical significance.
** 5% statistical significance.
* 10% statistical significance.

reaches a steady state—or more accurately, given the randomness, proceeds to a central tendency.[22] To avoid random outcomes, we average over the final 100 periods at the end to get the long-run estimate.

To illustrate the dynamics from selection, we use a simple, non-rational model of insurance company behavior. We assume that insurance premiums are based on average family costs across the

[22] Empirically the quasi-steady state is reached relatively quickly.

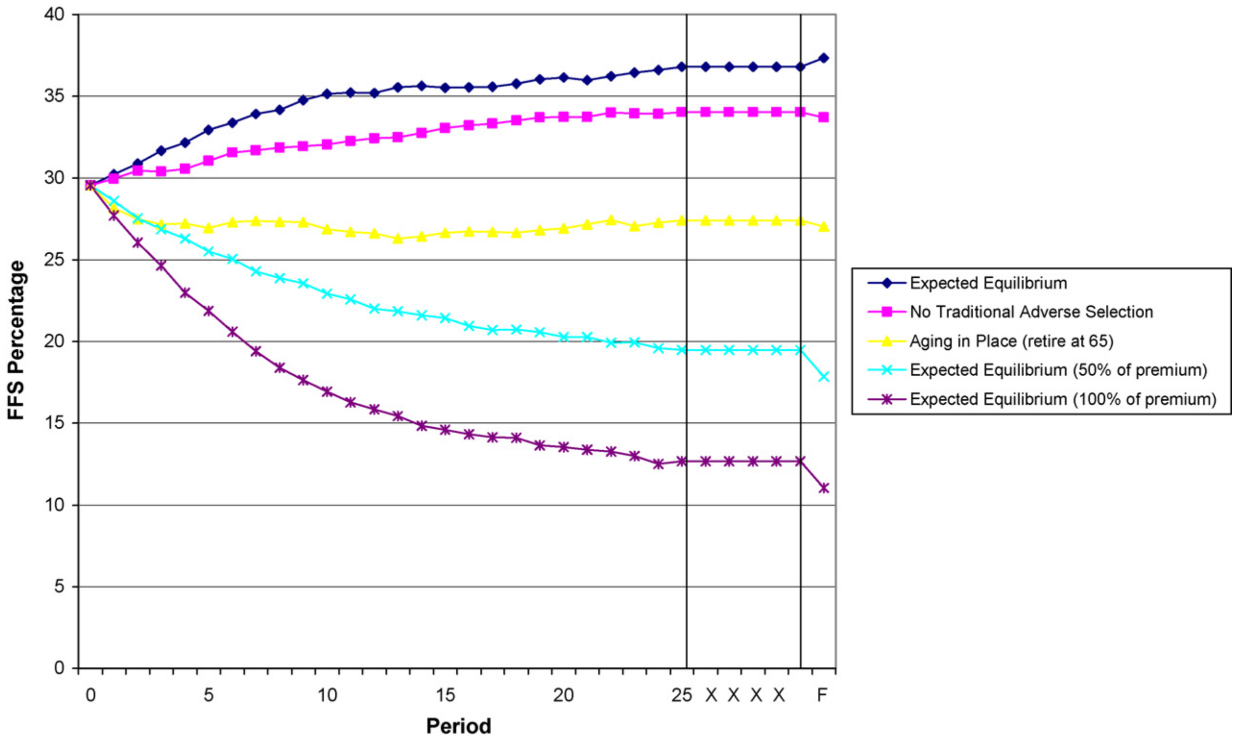

Fig. 6. FFS percentage dynamics. *Notes*: The periods labeled "X" before the last point are just kept at period 25 for visual convenience. The last point labeled "F" is the final equilibrium.

Table 5
FFS enrollment in different equilibria.

Simulation	Employee share of premium		
	15%	50%	100%
Baseline	29.5%	29.5%	29.5%
Equilibrium	37.3	17.9	11.0
No spending effects	36.6	17.3	10.5
No traditional adverse selection	33.7	15.5	9.3
No extrapolation	40.7	19.8	12.5
Aging in place	27.0	19.0	15.1

Notes: 15% is the current employee share of the premium. Population is a random sample from year 2003 enrollment.

plan as a whole, plus a 10% administrative load. The premium to families reflects the long-term GIC marginal subsidy of 85%; we later explore other subsidy levels. A more sophisticated model would have plans try to anticipate what their premium pricing would do for future selection. To do this, they would need also to conjecture their competitor's policy, leading to a game-theoretic oligopoly situation. It is an empirical question of how much current health insurance companies consider and use less naïve strategies than those assumed in our model, and how much public policy affects that. For now, we use the simpler assumption.

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% individual share of the premium—the current GIC sharing rule. The remaining columns show what happens if that share is increased to 50% and then to 100%.

The first row gives the baseline share in the FFS plan from our population sample drawn from 2003, namely 29.5%. Running the current model forward, we find an equilibrium FFS share of 37.3%, shown in the second row.[23] Fig. 6 shows the transition dynamics. The enrollment increase up to the equilibrium level effectively happens within 20 years.

The next three 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 36.6%, a very modest decrease. The next two rows turn off future and past spending as explanatory variables in the switching equations. Eliminating traditional adverse selection (where future spending affects plan choice), drives down the FFS share, while eliminating plan decisions based on past spending increases it. In each case, though, the changes are minor.

The final simulation examines the impact of complete retention, i.e., no one switches plans but people do age in place. To examine such aging in place, we need to add more dynamic structure. Each year, we increase everyone's age by a year. When an insured reaches age 65, we assume she and her family leaves the GIC. Other households leave before age 65. To capture those members, we estimate a logit equation for the probability that a member leaves the GIC altogether. 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. A random draw determines which families leave the GIC before age 65, based on the predictions from the exit equation. To hold the total GIC population constant, we draw new entrants from our entrant pool data to just equal the numbers of those who exit. We iterate the model to find the steady state.

As Fig. 6 and Table 5 show, enrollment in the FFS plan falls to 27% over time. The drop in FFS enrollment is due to both the dif-

[23] The constant term for switching between plans differs by year. The steady-state share in the FFS plan thus differs by which year's coefficients are used. In the simulations, we use the average of all year dummies.

ferentially older folks in the FFS exiting in higher proportions, and the relatively young entrant population, who tend to choose the HMO. In the aging scenario, the plans will cycle in and out of relative importance. As the FFS plan enrollees retire, the relative cost of that plan falls, and more new entrants will enroll in it. Fig. 6 shows that this cycling 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% subsidy, we estimate that equilibrium enrollment in the FFS plan to be 37%. If the GIC reduced its subsidy to 50% of the premium differential, in contrast, the selection effect would be immense. We estimate that enrollment in the FFS plan would fall to 18% in that scenario. If the employee had to pay the entire marginal cost of the FFS plan, as insurance plans at many workplaces require, we estimate FFS enrollment at only 11%. The selection that results from premium increases comes from the greater attachment of higher cost individuals to the FFS plan. Valuing the FFS plan more, higher cost people are less like to leave as prices rise. Because of its then much sicker and older population, this reduced enrollment would bring with it a very large increase in FFS premiums.

6. Conclusions

Pooling of heterogeneous individuals into several health plans can lead to a variety of different equilibria, depending on how people select plans. Examining data from the GIC, we show that adverse selection substantially outweighs adverse retention as an influence. 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, selection is always against the FFS plan.[24]

Still, these effects are small relative to the impact of changes in the mix of employer and employee premium payments, implying that changes in GIC rules on premium sharing could be significant. Moving from an 85–15 sharing rule to the commonly observed arrangement 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 dwindle to oblivion. Premium structures are important, especially as they promote 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 formidable. We suspect that there is a salience feature at work. When premiums change suddenly and by large amounts, people are induced to think about their health plan choice. Since this thinking works to promote adverse selection, big system changes tend to induce dramatic responses, larger in proportion than little system changes.

Our results also have implications for risk adjustment, an arrangement that most health economists believe is vital to efficient operation of insurance exchanges. 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 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.

Appendix A. 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 0–4, 5–19, 20–34, 35–49, 50–60, and 61–65. 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 3-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. To address this, we find the 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. The estimated coefficient for FFS spending to be indexed to HMO spending is .737.

The variable copay at the individual level has a small number of extremely large values (a few are tens of thousands of dollars and up.) We take the 99.99 percentile ($3685) and truncate the 297 observations above this level to that percentile. There is no effect on all other coefficients from this change.

The FFS plan and the various HMOs all had broad networks and similarly generous benefits in this period.

For our logistic equation results, as well as for showing coefficients and standard errors, we present the relative risk of the associated variable: the 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 16.8 and for copays $366. Among demographic variables the omitted category in equations at the individual level 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 omitted 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.

[24] In Cutler and Zeckhauser (1998) two of the authors showed that aging in place could be important in the equilibrium, as we show here. That paper referred to aging in place as adverse retention. In this work, we differentiate between risk-based retention and the impact of differential aging assuming no mobility.

Table A1
The evolution of spending.

Variable	Probability of use		ln(spending) if use	
	HMO	FFS	HMO	FFS
Intercept	2.643***	3.785***	5.734***	6.149***
	(0.020)	(0.043)	(0.009)	(0.017)
Visits lagged	0.027***	0.018***	–	–
	(0.002)	(0.002)		
Copay lagged	0.007***	0.007***	–	–
	(0.000)	(0.000)		
Demographics (omitted category is male 0–4)				
Male 5–19	−0.409***	−0.482***	−0.146***	−0.032***
	(0.018)	(0.041)	(0.006)	(0.012)
Male 20–34	−0.756***	−1.037***	−0.110***	0.075***
	(0.019)	(0.043)	(0.007)	(0.015)
Male 35–49	−0.632***	−0.653***	0.155***	0.341***
	(0.018)	(0.042)	(0.007)	(0.013)
Male 50–60	−0.526***	−0.516***	0.535***	0.644***
	(0.020)	(0.042)	(0.007)	(0.012)
Male 61–65	−0.625***	−0.547***	0.689***	0.675***
	(0.026)	(0.043)	(0.011)	(0.013)
Female 0–4	−0.022	−0.014	−0.101***	−0.072***
	(0.025)	(0.056)	(0.008)	(0.015)
Female 5–19	−0.316***	−0.376***	−0.138***	−0.013
	(0.019)	(0.043)	(0.006)	(0.012)
Female 20–34	−0.301***	−0.527***	0.369***	0.357***
	(0.020)	(0.044)	(0.007)	(0.013)
Female 35–49	−0.329***	−0.355***	0.411***	0.531***
	(0.019)	(0.042)	(0.006)	(0.012)
Female 50–60	−0.395***	−0.347***	0.634***	0.679***
	(0.021)	(0.042)	(0.007)	(0.012)
Female 61–65	−0.943***	−0.502***	0.682***	0.621***
	(0.025)	(0.043)	(0.010)	(0.012)
Lagged Indexed spending (omitted category is the first decile—lowest positive spending)				
Negative spending	−0.323***	−0.956***	0.734***	1.137***
	(0.094)	(0.127)	(0.068)	(0.097)
Zero spending	−1.743***	−2.089***	0.105***	0.250***
	(0.010)	(0.016)	(0.006)	(0.011)
Second decile	0.282***	0.174***	0.175***	0.279***
	(0.011)	(0.019)	(0.006)	(0.010)
Third decile	0.470***	0.410***	0.344***	0.481***
	(0.013)	(0.021)	(0.006)	(0.010)
Fourth decile	0.616***	0.619***	0.535***	0.708***
	(0.015)	(0.025)	(0.006)	(0.010)
Fifth decile	0.712***	0.810***	0.736***	0.940***
	(0.017)	(0.028)	(0.006)	(0.009)
Sixth decile	0.816***	0.934***	0.951***	1.181***
	(0.020)	(0.032)	(0.006)	(0.009)
Seventh decile	0.843***	1.047***	1.170***	1.420***
	(0.023)	(0.037)	(0.006)	(0.009)
Eighth decile	0.798***	1.068***	1.415***	1.701***
	(0.026)	(0.041)	(0.006)	(0.009)
Ninth decile	0.639***	1.031***	1.655***	2.013***
	(0.028)	(0.046)	(0.006)	(0.009)
Tenth decile (highest spending)	0.353***	0.745***	1.991***	2.553***
	(0.028)	(0.048)	(0.008)	(0.011)
N	1,656,041	753,382	1,349,009	645,383
Pseudo R^2/R^2	.292	.329	0.274	0.327

Notes: Data are for 1994–2004. Equations are estimated at the individual-year level. Year dummy variables are included. Indexed lagged spending is actual lagged spending for stayers, and for switchers the same adjusted to be comparable to spending as if they had stayed, see text and data appendix. Demographic variables are a dummy for indivdual in that age–sex group. Huber–White standard errors corrected for within family correlation across time are in parentheses.
*** 1% statistical significance.
** 5% statistical significance.
* 10% statistical significance.

Table A2
OLS estimates of other relationships.

Variable	Dependent variable	
	ln(1 + visits)	ln(1 + copay)
Intercept	1.967***	1.600***
	(0.070)	(0.003)
ln(1 + visits) lagged	0.469***	–
	(0.001)	
ln(1 + visits) contemporaneous	–	0.329***
		(0.002)
FFS	0.066***	−0.238***
	(0.002)	(0.002)
Demographics (omitted category is male 0–4)		
Male 5–19	−0.220***	–
	(0.004)	
Male 20–34	−0.199***	–
	(0.005)	
Male 35–49	−0.061***	–
	(0.004)	
Male 50–60	0.094***	–
	(0.005)	
Male 61–65	0.212***	–
	(0.005)	
Female 0–4	−0.061***	–
	(0.005)	
Female 5–19	−0.185***	–
	(0.004)	
Female 20–34	0.020***	–
	(0.004)	
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	–	0.826***
		(0.107)
Zero spending	–	−0.368**
		(0.179)
Second decile	–	0.436***
		(0.002)
Third decile	–	0.816***
		(0.003)
Fourth decile	–	1.134***
		(0.003)
Fifth decile	–	1.404***
		(0.004)
Sixth decile	–	1.627***
		(0.004)
Seventh decile	–	1.849***
		(0.004)
Eighth decile	–	2.080***
		(0.005)
Ninth decile	–	2.289***
		(0.005)
Tenth decile (highest spending)	–	2.441***
		(0.006)
N	1,552,140	1,965,910
R^2	0.294	0.668

Notes: Data are for 1994–2004. Equations are estimated at the individual-year level. Year dummy variables are included. Spending is actual contemporaneous spending. Demographic variables are a dummy for indivdual in that age–sex group. Huber–White standard errors corrected for within family correlation across time are in parentheses.
*** 1% statistical significance.
** 5% statistical significance.
* 10% statistical significance.

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