Health Savings Accounts, Plan Choice, and Health Care Utilization: Simulating the Effects of HSA Introduction in Individual and Group Markets

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Abstract

Many policies and proposals for health care reform involve complex insurance products. For example, the Modernization of Medicare Act (2003) included two innovations: 1) health savings accounts, but only if accompanied with high-deductible health insurance policies; and 2) Medicare Part D coverage for prescription pharmaceutical products with an associated donut-hole. Future proposals are also likely to involve complex insurance products interacting in complicated ways with the tax system. Current methods for evaluating and predicting the implications of such policies tends to treat insurance as a homogeneous, stand-alone product. It is likely that prediction and evaluation can be substantially improved by accounting for important complexities.

Our research introduces a straightforward methodology to evaluate a variety of complex insurance products. Specifically, we evaluate the implications of introducing Health Savings Accounts coupled with high-deductible policies. A novel aspect of our approach is a calibration of underlying preference parameters that allow us to simulate how consumers will value products like high-deductible insurance and HSAs. We focus on three groups of particular policy interest: 1) the currently uninsured who do not have access to group coverage, 2) the currently uninsured who have access to group coverage, but choose to be uninsured, 3) the currently insured in group coverage.

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1 Introduction

In December of 2003, Congress passed the Modernization of Medicare Act which had as a primary goal the addition of a prescription drug benefit to the Medicare program. But the legislation also included a provision establishing health savings accounts (HSAs). Such accounts, when coupled with a catastrophic high deductible health insurance policy (CHP), allow individuals to avoid income and payroll taxes for qualified medical expenditures.

There have been a number of proposals to make HSAs and high-deductible health insurance policies more affordable and attractive for the currently uninsured. For example, current proposals include the following: 1) create an income tax deduction for the premium on a HSA-qualified insurance policy, 2) create an income tax credit for HSA-qualified policies purchased outside the employment-based group market, and 3) increase the allowable annual HSA contribution amount. (State of the Union Address, January 31, 2006). The first two proposals would lower the cost of insurance by extending the tax subsidy to those not purchasing insurance through employers; and the third proposal was later signed into law.

While these proposals would likely lower the cost for HSA-qualified insurance, it is unclear whether such proposals would actually decrease the number of uninsured. The tax-based policies noted above are designed to eliminate the tax advantage currently available to employment-based insurance. But employment-based insurance pools also economize on underwriting costs and help to reduce the potential for adverse selection. Some analysts have argued that eliminating that differential could adversely affect the employment-based market, causing firms to offer less attractive policies to employees, resulting in lower take-up rates, or to drop coverage altogether (Moon et al., 1996; Zabinski et al., 1999; Glied and Remler, 2005; Hoffman and Tolbert, 2006). The net effect could be a weakening of these pools and an increase in the number of uninsured.

We will explore the impact of HSAs and the various tax proposals on the uninsured population, including the effect of how adopting the tax deduction and credit policies for non-group insurance would affect the employment-based group market. The foundation for our work is a recently developed simulation model based on utility-maximizing, representative agents (Cardon and Showalter, 2007). From our previous work, it is apparent that the form of the HSA contract, which depends both on Federal regulations and employer choices, is important in determining whether the introduction of HSAs undermines traditional insurance pools and differentially affects individuals based on their health status. These issues will have important implications for determining the ultimate impact of these proposals on the uninsured population.

The main advantage of our framework over previous simulation models is the ability to determine consumers' valuation of products for which little or no data exists-e.g. HSA contributions and high-deductible insurance. This is accomplished through empirical calibration of parameters of consumer preferences and the risks associated with uncertain medical expenditures. Given these estimates we are better able to extrapolate to new products or policies.

To illustrate, consider the problem of assessing the impact of various HSA-linked proposals. It is critical to have an estimate of consumers' price elasticity of high-deductible policies. But there are no generally accepted estimates of this elasticity due to the paucity of data on such policies. Thus previous work has been forced to use elasticity estimates based on more traditional insurance; but it is not clear these elasticities will be similar. Our methodology can adjust for such differences because it is based on consumers' underlying risk preferences.

We focus on three consumer groups of particular policy interest: 1) the currently uninsured who do not have access to group coverage, 2) the currently uninsured who have access to group coverage, but choose to be uninsured, 3) the currently insured in group coverage. For each group, we the Medical Expenditure Panel Survey to assess representative values for demographic variables such as income, age-specific health expenditures, and tax rates. For each group, we will then calibrate our model to match the observable characteristics. Then we model a variety of policy changes and assess the value of each change to consumers and their likelihood of changing from the status quo.

2 Related Simulation Approaches

Several methods have been used to estimate the impact of various health policy proposals. Glied et al. (2002) provide a useful summary of the literature, which we follow in this section.

The Elasticity Approach

This is the most widely used method. It typically uses individual-level data, and in highly simplified terms it can be described as having three steps: 1) estimate the impact of a policy change on prices and income for individuals; 2) compute the change in demand, given the Step (1) change, using elasticity estimates for insurance demand (or other behavioral responses); 3) aggregate across individuals, with the appropriate weighting, to get national estimates.

The Discrete Choice Approach

This method uses a binary choice regression framework where the dependent variable is 1 if a person has insurance, and 0 otherwise. Observable characteristics of the individual (age, income, gender, employment status, etc) and a measure of insurance price are used as explanatory variables. This methodology is similar to the elasticity approach, except that the elasticity estimate is embodied in the regression parameters and the functional form of the specification. The procedure is roughly as follows: 1) estimate the initial regression model which will specify the elasticity; 2) estimate the impact of the policy change on prices and incomes for individuals; 3) estimate the change in the probability of being insured using the data from Step (2) in the regression model of Step (1); 4) aggregate across individuals to get national estimates.[1]

The Matrix Approach

This method uses grouping of individuals, applies group-specific take-up elasticities, and then aggregates to get national estimates. The estimation steps include: 1) estimate the impact of the policy change on average prices and incomes for each group; 2) compute the change in demand for each group, using group-specific take-up elasticities; 3) aggregate across groups to get national estimates.

[1] An interesting recent example of this approach is Feldman et al. (2005) which estimates a conditional logit model of HSA takeup rates for employees in three large firms. They use the estimated model to simulate take-up rates in the group and non-group markets. Health Reimbursement Arrangements (HRA) are used as a proxy for HSA choice since HSAs were not an option for the employees in their data. Their simulations predict a 9 percent HSA take-up rate in the non-group market, but a very low take-up rate in the group market. A refundable tax-credit for HSAs is predicted to double the HSA take-up rate while lowering the number of uninsured by 8 percent.

The Reservation Price Approach

This category uses indirect approaches to measure how utility changes with a given policy option. The measured change in utility is then used to estimate behavioral responses. The two primary methodologies are Zabinski et al. (1999) and Pauly and Herring (2002). Zabinski et al. (1999) use a linear approximation to the change in utility, combined with income and price changes from a given policy, to estimate whether a given individual will switch from a 'standard' insurance policy to high-deductible insurance policy coupled with a medical savings account. Pauly and Herring use a revealed preference argument to estimate how individuals would respond to a tax credit for health insurance. Both of these indirect approaches are tailored to answer specific questions and are not easily comparable to the first three general approaches.

Discussion

Remler et al. (2002) works through an example that shows that the first three methods give roughly the same results if the underlying data and elasticity estimates are the same. One important feature of the first three methods is that there is little scope for variation in insurance policies; to a first approximation, an individual is treated as having insurance or not; there is generally no attempt to account for variation in policy generosity and how consumers might value policy generosity.

Policy generosity is now at the center of the public debate. "Consumer directed health care" focuses on the advantages of high-deductible policies over more traditional insurance. But the framework and data used for currently available simulations are ill-suited for analyzing the impact of such policies. The estimation shortcomings are even more acute when trying to account for tax-subsidized financial accounts like health savings accounts, health reimbursement accounts, and flexible spending accounts. These accounts are explicitly designed to work in conjunction with insurance policies, but no data exist to allow researchers to understand how consumers view the tradeoff between money in a tax-preferred account and the generosity of insurance.

Of the reservation price approaches, it is not clear how the Pauly/Herring approach could handle policy innovations like health savings accounts, since the accounts, which are critical part of overall coverage, are not part of traditional plans. The Zabinski et al. (1999) article is an explicit attempt to measure the impact of HSAs, but the linear approximation approach embodies strong assumptions about the value of HSAs accounts which seem to overstate their attractiveness..[2]

In the next section we outline a framework for evaluating the impact of recent policy innovations such as health savings accounts and high-deductible policies. Our framework is explicitly based on a utility maximization assumption and this allows us to explore how consumers would react to new policy choices for which no data exists. The calibration of the model is done using observable data so the utility parameters have an empirical foundation, but they allow much greater flexibility in simulating policy options than is possible using current methods.

Our approach can be thought of as a combination of existing methodologies: We group consumers into identifiable demographic categories based on observable characteristics (e.g. income, age, employment status, etc) like the Matrix Approach. Each group is then modeled with a representative agent who maximizes utility, similar to the Reservation Price Approach, except we use a specific form of utility rather than an approximation to a change in utility. Within each demographic category, we then use a discrete choice framework to model the selection between being insured and uninsured, accounting for utility gain or loss given a particular policy proposal.

3 Approach and Methodology

We begin by describing our utility-maximizing framework which will be applied to each demographic group. Our model accounts for the uncertainty inherent in making choices about insurance, and is dynamic: choices made in one period affect outcomes and utility in later periods.

Preferences

Utility in each period is derived from the consumption of a composite consumption good, C, and Health. Health is determined by a random health state θ and "health services," X. θ denotes the random health status which determines the relative value of health expenditures. The utility function is a modest generalization of a standard constant elasticity of substitution utility function.

[2] Their model predicts that even without the tax advantage, most consumers would choose to have a high-deductible policy and a health savings account.

For a single period it is

$$U(C,H) = \frac{C^\lambda - 1}{\lambda} + \gamma\frac{(X-\theta)^\lambda - 1}{\lambda},$$

where health $H = X - \theta$. The structure on utility implies that optimal X will not be less than θ. Note that the higher the value of θ, the higher will be marginal utility of health services in that period. Were this a single-good model, $1 - \lambda$ would also be the coefficient of relative risk aversion. With two goods, however, the interpretation of $1 - \lambda$ is not precisely the same; but we will treat it as an approximate measure of risk aversion when interpreting parameters. The parameter γ accounts for the relative value of health compared to C.

Dynamic Optimization Problem

For tractability we assume there are two periods denoted by subscript t: in period 1, a consumer knows her health status for that period, but health status in period 2, θ_2, is unknown. An insurance policy for period 2 consists of a coinsurance rate, α_2, and a deductible, D_2. In period 1, the consumer chooses the following:

1. How much of good X to consume in period 1 (X_1).

2. How much to withdraw from the HSA balance available in period 1 to pay for period 1 health services (W_1).

3. How much of period 2 income to allocate to the HSA in period 2 (Z_2).

The HSA balance in period 2, M_2, is determined by current contributions, Z_2, and the return on unused balance from the previous period according to the equation $M_2 = Z_2 + (M_1 - W_1)(1 + r)$, where r is the interest rate on HSA balances. The insurance policy will be associated with a premium, P_2, which includes a loading factor. Withdrawals, W_2, are limited by the account balance and by out-of-pocket costs, $O(X_2)$, defined below. Given these choices, the consumer in period 2 then chooses optimal health expenditures for period 2, X_2, and the withdrawal W_2 conditional on the realized health state, θ_2. C_2 is determined by the budget constraint.

The objective function in period 1 problem is given by

$$EU = \frac{C_1^\lambda - 1}{\lambda} + \gamma\frac{(X_1-\theta_1)^\lambda - 1}{\lambda} + \beta E\left[\frac{C_2^\lambda - 1}{\lambda} + \gamma\frac{(X_2-\theta_2)^\lambda - 1}{\lambda}\right] \tag{1}$$

with constraints

$$M_2 = Z_2 + (M_1 - W_1)(1+r) \tag{2}$$

$$C_1 = (Y_1 - P_1 - T_1) - O(X_1) + W_1 \tag{3}$$

$$C_2 = (Y_2 - P_2 - Z_2 - T_2) - O(X_2) + W_2 \tag{4}$$

$$0 \leq W_t \leq M_t \tag{5}$$

$$W_t \leq O(X_t) \tag{6}$$

$$O(X_t) = \begin{cases} X_t: & X_t < D_t \\ D_t + \alpha_t(X_t - D_t): & X_t \geq D_t \end{cases} \tag{7}$$

The values θ_1, M_1, Z_1, P_1, D_1, α_1 are known and given as of time 1. β is the one period discount rate, and T_t is the total tax, which is a function of the marginal tax rate, τ[3]. Think about solving this by backward induction. In period 2 there is no HSA contribution ($Z_3 = 0$), because we consider a 2-period model. Instead, after θ_2 is revealed the consumer chooses X_2 and the optimal withdrawal W_2 to maximize

$$\frac{C_2^\lambda - 1}{\lambda} + \gamma\frac{(X_2-\theta_2)^\lambda - 1}{\lambda}$$

subject to (2) and (4)-(7). Moving back to the first period, prior to observing θ_2, the consumer chooses X_1, W_1, and Z_2 subject to (2)-(7) and assuming optimal period 2 choices. Note that maximizing (1) assumes optimal choices for health expenditures as well as optimal usage of the HSA account for HSA policies in both periods. Traditional insurance (and no insurance) are special cases of this model and that optimal behavior for these cases can be computed using the same method. The optimized value of (1) is EU^*.

The use of tax-preferred accounts like HSAs is intuitively a multi-period problem. Indeed, some observers have noted that HSAs could act as a useful retirement savings vehicle (Furman, 2006).

[3]We use an algorithm based on NBER's TaxSim model to compute taxable income, total taxes, and marginal tax rates.

We approximate a long-horizon dynamic model by allowing conversion of unused HSA balances to consumption after paying taxes plus a penalty, similar to the treatment of early IRA withdrawals. The justification comes from the theoretical framework found in Cardon and Showalter (2007): in an infinite horizon model, the expected marginal utility per dollar (accounting for taxes) will generally be equalized across X_t, C_t, and the discounted value of M_{t+1}, because the marginal dollar could be spent on any of those commodities. We therefore set the model to allow the representative agent to consume as C_2 any unused HSA balance in the second period at a rate of \$1 of HSA convertible to \$ $(1-\tau)(1-Penalty)$ of C_2. We simulate the model using $Penalty = .055$. We obtain this by assuming that unused balances earn interest at interest rate $r = .05$ and are discounted using $\beta = 0.9$, yielding $(1-Penalty) = \beta(1+r) = 0.945$. We label this "recovery" factor π. Setting $\pi = 0$ turns the account into a use-it-or-lose-it FSA[4].

Deductibles will induce a kink into the usual linear budget constraint; a positive HSA balance will create a second kink. These non-linearities create a serious challenge for optimization. Consider the kinked budget sets for HSAs in two cases below. The case of a low HSA balance, where $M_2 \leq D_2$, is shown in Figure 1. Slopes and the intercept depend on the $Penalty$, where $(1-Penalty) = \pi$. For the first segment between the vertical intercept and point a, the slope is $-(1-\tau)\pi$. At point a the account is exhausted, and the slope changes to -1 up to point b. At point b the deductible is reached and therefore the slope beyond b is $-\alpha_2$. For a very healthy person (low θ_2), health care consumption is zero, and $C_2 = Y_2 - P_2 - (1-\pi)Z_2 - T_2$. If the penalty is zero, or if $\pi = 1$, then there is no penalty for the unused balance, and consumption would be as if $Z_2 = 0$. For higher values of θ_2, indifference curves flatten and the optimal bundle will move down the budget constraint. Optimal behavior with convex preferences implies a concentration at a, since many values of the health state will imply consumption at the kink.

[4]The resulting consumption expenditures, C_2, will be too high relative to what we would find with an infinite horizon model (because the agent allocates to C_2 what would have been allocated to M_3), but expected utility, health expenditures, and HSA balances should be a better approximation than not allowing any conversion.

Figure 1: Budget Sets for $M_2 \leq D_2$

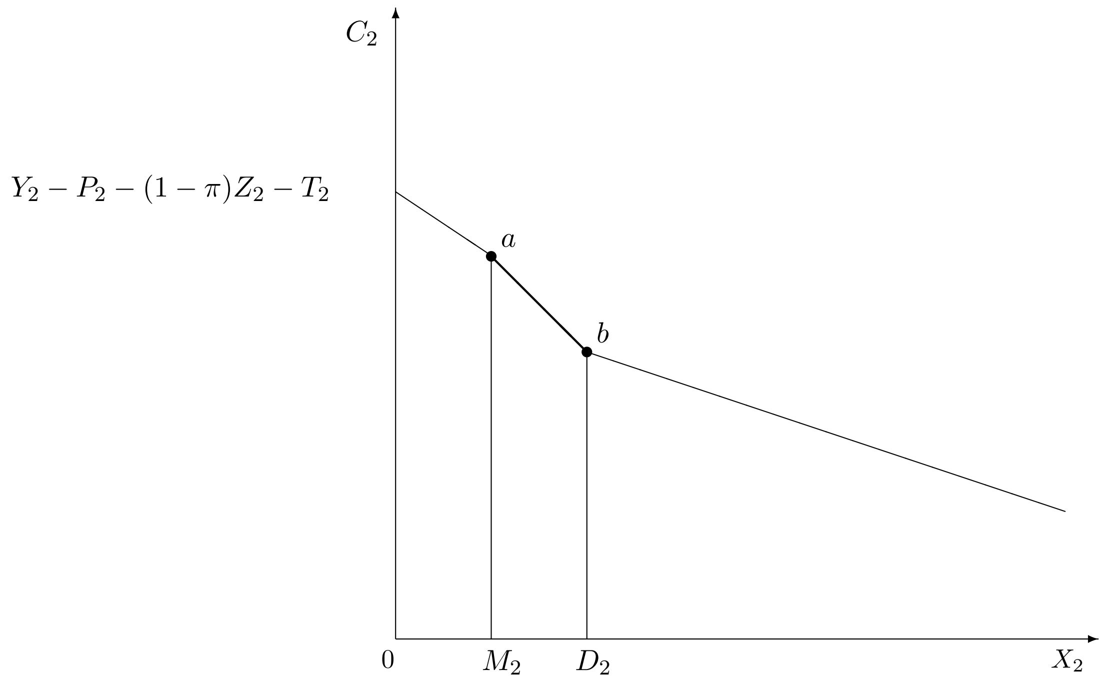
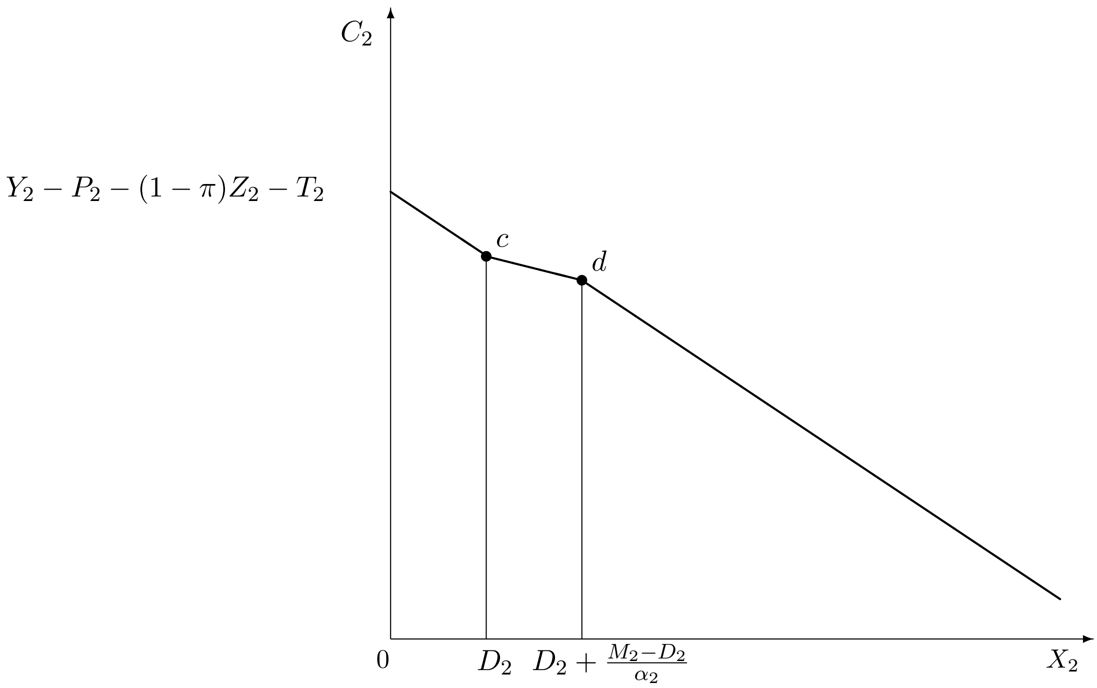


Figure 2 shows the case where HSA balances are large, $M_2 > D_2$. The slope between the intercept and point c where the deductible is reached is $-(1-\tau)\pi$. Between points c and d the consumer pays only the coinsurance rate α_2 and is paying all out-of-pocket expenses from the account, hence the slope is $-(1-\tau)\alpha_2\pi$ until the account is exhausted at point d. Beyond d the slope is $-\alpha_2$.

Figure 2: Budget Set for $M_2 > D_2$



Health State Distribution

Health type is determined by the distribution of θ. There are obviously a variety of ways that the distribution of θ could be modeled. Ideally, we would like to generate a distribution of expenditures that is similar to observed patterns of health expenditures, which is positively-skewed with a mass at zero.

Health expenditures are nearly linear in θ for the specified utility function, so by choosing a distribution for θ which is right-skewed and has a mass at zero, we obtain a similar distribution for health expenditures. We therefore model θ as coming from a mixture distribution of the following form:

$$\begin{aligned} \theta &= 0 \text{ with probability } p \\ &= \Theta \text{ with probability } 1-p \end{aligned}$$

where Θ is lognormal random variable with mean μ and variance σ^2.

Simulation Model

Due to the complexity of the problem, closed-form analytic solutions are not possible and we therefore proceed by developing a computer simulation model. One complication that arises in the simulation of equation (1) is the specification of the insurance contract. We assume the insurance contract arises out of a competitive process with proportional loading so that the premium for an insurance contract with deductible D and coinsurance rate α is proportional to an actuarially fair contract. But this premium will depend upon the expected expenditures in period 2, which are endogenous. We overcome this difficulty by using the following algorithm to compute a rational expectations equilibrium: 1) Choose a 2nd period insurance contract (α_2, D_2) and premium, P_2. 2) Maximize expected utility subject to that particular insurance contract. 3) If expected insured outlays exceed the premium, re-estimate with a higher premium; if the premium exceeds the expected outlays, re-estimate with a lower premium. Steps (1)-(3) are repeated until convergence of the premium. For group insurance, the pooled premium depends on the expected expenditures of consumers in the group, and the algorithm is modified accordingly to reflect group composition.

4 Setup and Calibration

Since the simulation model is programmed to determine optimal behavior for individual households, we simulate behavior for households of different types broken down by age, family size, income, and educational attainment. For each "cell" of similar households we use data on health care utilization from the Medical Expenditure Panel Survey (MEPS) to obtain estimates of the unknown parameters of the utility function (λ and γ) and the distribution of health states (μ and σ^2)in the following way. We observe the sample mean and variance of expenditures for each cell, and we have estimates of the population price and income elasticities of health expenditures from the RAND Health Insurance Experiment. We obtain method of moments estimators for the 4 parameters by matching these sample moments with theoretical moments (which are functions of the parameters to be estimated) implied by the period utility function $U(C,H)$ above.[5] Using this method we can match the mean and variance of expenditures (measured in $1,000s) as well as price and income sensitivity in a simple, flexible way. To estimate $p = Pr(\theta = 0)$ we simply use the frequency of zero expenditures for each cell. We will use estimates available from the literature on time preference to set $\beta = 0.9$.[6]

In the current version of the model we use 300 cells: 10 income deciles, an age indicator for whether the head of household is Younger (age$\leq$ 40) or Older (age$>$ 40), indicators for 5 family size groups, and indicators for 3 levels of education (No Degree, High School Degree, and College Degree). Table 1 shows theoretical and sample moments and the resulting estimates. We compute different values of the risk and preference parameters for 10 age/income cells.

Simulation

Each cell is characterized by a set of parameters for utility and risk, and a set of insurance options. For those not offered group insurance, the choice set is

{No insurance, Public Insurance, Non-group Private,}

while for those offered it is

{No insurance, Public Insurance, Non-group Private, Group Insurance}

The characteristics (price, cost-sharing, etc.) of these options will vary across cells according to employer choices (such as the decision to offer insurance and how much of the premium to pay) and public insurance eligibility.

[5]The demand function for health expenditures is $X^* = \frac{Y+K\theta}{K+\alpha}$ This implies that the $E(X^*) = \frac{Y+KE(\theta)}{K+\alpha}$ and $Var(X^*) = (\frac{K}{K+\alpha})^2 Var(\theta)$. Price and income elasticities are the standard definitions evaluated at the mean of θ. See Table 1. Elasticities could, in principle, vary across cells, but in this version they were set at $\varepsilon_p = -0.15$ and $\varepsilon_Y = 0.2$ for all cells. With more data it would be feasible to estimate distinct $(\mu, \sigma^2, \lambda, \gamma)$ for each cell.

[6]Typical estimates range from 0.80 to 0.95.

Taking estimated (calibrated) parameters as given, we run the simulation model for cell i and option j, which yields a simulated utility, δ^*_{ij}. This represents the component of expected utility that can be explained by the simulation model. We repeat this for cells $i = 1, ..., I$ and for the range of options $j = 0, ..., J_i$ in the choice set for cell i, including option 0, which is no insurance of any type. To account for unobserved factors, including behavioral factors and other heterogeneity, we include option-specific random taste shocks, a_{ij}. If this were a conventional discrete choice model, the variance of the shocks would need to be normalized and the coefficients of the model scaled to be in the same units. Here the scaling of the δ^*_{ij} from the simulation model are in the (arbitrary) units of the utility function. We assume that expected utility V^*_{ij} is a function of δ^*_{ij}, option- and cell-specific dummy variables Δ_{ij} and the random taste shocks:

$$V^*_{ij} = EU^*_{ij} + a_{ij} = \beta_j \delta^*_{ij} + \xi'_{ij}\Delta_{ij} + a_{ij}, \quad \text{for} \quad i = 1, ..., N \ \text{ and } \ j = 0, ..., J_i. \tag{8}$$

The scale parameter β_j, which we allow to vary across options, adjusts the scale of δ^*_{ij} so that it is in the same units as the (normalized) taste shocks. We then estimate the unknown parameters of (8) using a multinomial discrete choice model. Inclusion of a rich set of dummy variables (including those for income deciles, family size, and education) enables us to account for cell and option specific factors that the simulation model has not captured. We are then able to match observed market shares.

Finally, having simulated the market shares P_{ij} as the probability that consumer i chooses option j from data, we add the HSA option to the choice set, simulate $V^*_{i,HSA}$ for each cell, and recompute the probabilities. Comparison of these probabilities with the initial set allows us to predict the effects of HSA introduction.

Distributional Assumptions

If we assume the option-specific shocks a_{ij} are independent (over both i and j) and identically distributed Type 1 extreme-value random variables then model (2) is the conditional logit. The probability that individual i chooses option j is :

$$P_{ij} = \frac{e^{V_{ij}^*}}{\sum_{k=0}^{J_i} e^{V_{ik}^*}}. \tag{9}$$

The advantage of the conditional logit model is the simple, closed form of the probabilities (9) and the straightforward way to add new options to the choice set. If cell i initially has J_i options but a new option $J_i + 1$ with utility V_{i,J_i+1}^* is added, then the new probabilities are easily computed as

$$P_{ij}^{'} = \frac{e^{V_{ij}^*}}{\sum_{k=0}^{J_i+1} e^{V_{ik}^*}}. \tag{10}$$

However, as is well known, the relative probability–or relative market shares–of any two options is independent of the addition of the new option, since the ratio reduces to

$$\frac{P_{ij}'}{P_{ik}'} = \frac{e^{V_{ij}^*}}{e^{V_{ik}^*}}$$

for any j and k. If options j and k are in the original choice set, independence of irrelevant alternatives (IIA) implies that their *relative* probabilities will remain unchanged regardless of the nature of the new option. This is a consequence of assuming that the taste shocks a_{ij} are independent.

Multinomial Probit Alternative

A more flexible alternative is the multinomial probit allowing for correlation of errors across options. This will reduce the influence of distributional assumptions on substitution patterns. Given the set of δ_{ij}^*, we estimate (8) assuming $\mathbf{a_i} = (a_{i0}, a_{i2}, ..., a_{1,J_i}) \sim N(\mathbf{0}, \mathbf{\Sigma})$ on observed market shares to get estimates of the scale parameters (β_j), dummy variable coefficients, the baseline market shares P_{ij}, and the covariance matrix Σ. We then augment the covariance matrix to form $\hat{\Sigma}^A$ using plausible values for correlations between the original options and the new HSA options. We then use Monte Carlo simulation to estimate the new probabilities, P_{ij}'.

The simplest way to do this is as follows. For each cell i take a draw $\epsilon_{\mathbf{it}}$ from the multivariate normal random distribution $N(\mathbf{0}, \hat{\mathbf{\Sigma}}^{\mathbf{A}})$ to form

$$\hat{V}^*_{ijt} = \hat{\beta}_j \delta^*_{ij} + \hat{\xi}'_{ij} \Delta_{ij} + \epsilon_{ijt}$$

for each option in the new HSA-augmented choice set for that cell. The predicted choice for each draw is the option that yields the highest $\hat{V}$. Repeat this for T draws of $\epsilon_{\mathbf{i}}$ and compute new market shares P'_{ij} as the frequency with which each option is chosen.

5 Results

Tables 2 and 3 present results from a multinomial probit model. We assumed homoskedastic errors but allowed for a single off-diagonal covariance term for all options. The estimate for the correlation across insurance plans is $\hat{\rho} = .5051$. These preliminary results assume that the premium paid by each family is risk adjusted for age, income decile, and family size. Estimating take-up rates with individual pricing tells us the underlying attractiveness of HSAs for each group. Later we will examine the group market in which premiums reflect the risk characteristics of the group, thus introducing the selection issue.

Table 2 gives the results for the individual market, households that do not have the option of employer-provided insurance. Each row corresponds to a demographic category defined by age (less than 40 and 40+) and income. To do this we took the mean over family size and degree cells for each income decile. The percent uninsured, publicly insured, and privately (non-group) insured predicted by the model are given in columns (1), (2), and (3), respectively. Columns (4)-(7) recompute the shares after a non-group "HSA policy" is introduced, which includes both a high-deductible policy (30 percent coinsurance, \$3,000 deductible, loading factor of 0.40) and a tax-preferred health savings account. We see that HSA take-up rates rise as income increases. For example, only 4 percent of the lowest decile, under 40 households choose an HSA while 28.5 percent of the highest decile households choose that option. This switch to HSA draws from all three previous options. For the lowest decile, the percent uninsured declines from 53.43 percent to 52.02 percent; the percent publicly insured declines from 42.1 percent to 40.3 percent; and non-group insurance falls from 4.4 percent to 3.6 percent. Older households display similar patterns: HSA take-up rises with income, drawing from all three original categories. Note also that for lower income households HSAs have higher predicted take-up rates than the non-group plan. The difference shrinks as incomes rise, and higher income deciles prefer the traditional plans. This is shown the the last two columns. HSA Share is the the fraction of privately-insured choosing HSA; HSA/NG is the ratio of HSA to non-group take-up rates. Only 7.68 percent of younger households in decile 1 choose private insurance, but 52.73 percent of those choose HSA. This measure of HSA attractiveness starts high and falls for both younger and older households. This means that while the HSA take-up rates increase with income, the relative attractiveness of HSAs decreases with income. It seems that HSAs are an inferior good in the individual market.

Table 3 gives the results for households who have the option of employer-provided insurance. These estimates are a preliminary exercise, since the each premium is adjusted for observable individual characteristics. The differences between these estimates and those in Table 2 are the employer subsidy (assumed to be 50 percent), the implicit tax subsidy, and the lower loading factor for the group market (18 percent instead of 40 percent). These households are modeled as having four options: no insurance, public insurance, non-group insurance, and group insurance. The simulation here adds a group HSA policy.[7] HSA take-up rates rise with income, but the attractiveness of HSAs relative to all private insurance declines with income, as HSA share falls for both younger and older households. For higher deciles Group and HSA take-up rates are roughly equal. Note that for Table 2 HSA Share starts high and falls, while for Table 3 HSA Share starts low and rises; both end up at just under 50 percent for both cases.

These preliminary results are suggestive that HSAs are attractive even to lower income households and have the potential to decrease the ranks of the uninsured. For example, in the individual market, HSA take-up rates for lowest five deciles are higher than non-group plans when both are available. Overall, the percentage uninsured declines from 59.4 percent to 55.5 for households not eligible for group insurance, and from 10.76 percent to 6.72 percent for those who are.

[7] We also experimented with adding a non-group HSA, but the percentages were so small that it made little difference.

6 Group Market Policy Simulations and Extensions

The above simulation results assume that insurance options are individually priced. This gives us a way to measure the attractiveness of such insurance. For the group market, however, insurance premia reflect the risk characteristics of the group, and there is potential for adverse selection. In particular, there is potential for HSA introduction to initiate a death spiral which drives out the traditional group plan. We now change the simulation strategy to reflect this.

We construct a firm's insurance pool by taking a sampling of households with different characteristics. We will continue to include no insurance and public insurance as options. We use the above framework as follows. Consumers evaluate each option by computing its expected utility

$$V_{ij} = \hat{\beta}_j \delta^*_{i1} + \hat{\xi}'_{ij} \Delta_{ij} + a_{ij}$$

where the hats denote that we are using estimates from the multinomial probit model above. The difference between the results above that those in this section is that here the δ^*'s depend on household characteristics and on the *pooled* premium. By integrating as above over draws of the error terms, we can compute initial market shares.

Next we add an HSA to the pool and let consumers move to their preferred plans. As premiums adjust, consumers update their optimal choices, and premiums adjust further. When this process converges we observe the new market shares and compare Group and HSA premiums in the new equilibrium with the original Group premium. We repeat the process for a variety of parameters, such as the composition of the firms (older, richer, etc.) and employer generosity. Note that the dummy variable coefficients $\hat{\xi}_{ij}$ estimated above are assumed to be equal for the Group policy and the newly-added HSA, so the difference in market shares is driven by the differences in δ^* alone.

6.1 First Stage Insurance Choice Results

The first set of results are found in Table 4. For these estimates we assume an employer is subsidizing insurance at a proportional rate of 50 percent. It is well known that proportional employer subsidy is better than a fixed dollar subsidy in avoiding potential adverse selection. Note also that since we aggregate medical expenditures the plans are identical in what medical conditions are covered[8]. For Table 4 we use the actual frequency counts from the MEPS data to weight each cell.

With a pooled premium, HSA take-up rates are higher than those in Table 3 for Younger households and slightly higher for Older households. Compared with Table 3, Group take-up rates are lower for younger households and higher for older households. HSA take-up rates rise with income, but HSA Share falls from 53.13 percent to 49.12 percent for the younger households and rises from 40.48 percent to the same 49.12 percent for the older households. Note that for a group plan all households pay the same premium. This means that younger, lower income households are paying a premium based on the average risk in the pool. Both types of insurance are likely to be unfairly priced for these households, and they are therefore more likely to prefer the lower-coverage HSA. As income and risk rise, the higher-coverage plan becomes more attractive. For older households it seems that the rise in relative shares is due in part to more aggressive use of the savings account as income and marginal tax rates rise. In fact, as we show in the next section, the lowest deciles have little incentive to contribute funds to the account. This would explain the jump in HSA take-ip after the first decile for older households. This same pattern holds for Tables 5 and 6 as well.

The original premium for the Group policy is $5,319. After HSA introduction, the Group premium *falls* to $5,286 and the HSA premium is $2,714. That is, the average makeup of the Group pool is not very different after HSAs are introduced, but what selection there is slightly advantageous. HSAs are a low cost alternative that do not offer first dollar coverage except through the account, which is self-funded. After the deductible is reached, however, the plans are similar. HSAs offer higher risk up to that point in exchange for a lower premium. Variation in take-up rates across cells reflects differences in the way households evaluate this tradeoff. Expected utilities are similar for many groups, so market shares are as well.

The makeup of the insurance pool should affect the potential for adverse selection. Table 5 shows results from a firm with a higher-risk pool made up of Older workers and only the lowest 4 income deciles of the Younger. As expected with a higher percentage of higher-risk, higher income

[8]See (Cutler and Zeckhauser, 1998)

households, the pooled Group premium rises to \$6,087 without the HSA option. When HSAs are offered, the HSA premium is \$3,193, but the Group premium falls to \$6,014.

Table 6 constructs a lower-risk firm made up of Younger workers and the lowest four income deciles of the Older workers. The Group premium rises from \$3,237 to \$3,246 when HSAs are offered, indicating a small amount of adverse selection. The HSA premium is \$1,481. Lower premiums compared with the uniform pool in Table 4 leads to overall higher insurance take-up, and HSAs lose much of their advantage.

Overall, we see that lower income households find HSAs attractive and that there appears to be no meaningful adverse selection, at least for the plan characteristics chosen for the estimation.

6.2 Second Stage HSA Balances and Health Care Utilization

Next we turn attention to HSA account contributions, balances, and withdrawals as well as health care utilization. Looking closely at HSA contributions, Z_2, we see that while lower income households do find HSAs attractive, they do not find it optimal to make use of the accounts. This is because for low income households the tax code does not provide any incentive to do so. Their marginal tax rates are low and their total taxes are, for the lowest deciles, negative when we account for the EITC. Further, we find that EITC phase-out rules lead to increasing marginal tax rates as we increase income, at least for the lowest deciles. For younger households, Z_2 increases from essentially zero to $\$4,257$. The different risk parameters of the older households lead to a similar if more abrupt pattern of increase, topping out at $\$6,007$.

We also present expectations of period 2 withdrawals W_2 and total health care expenditures for HSA, X_2, in the second and third columns. Recall that unused balances are not rolled over as in an infinite horizon model but are converted to current consumption after paying taxes and a penalty. This means that $E(W_2)$ is often substantially lower than Z_2. We interpret the difference as the expected rollover in an infinite horizon model. The ratio of average withdrawals to average contributions is 71.8 percent for the younger and 78.6 percent for older households. We conjecture that $E(W_2)$ is close to what would be the steady state contribution level in a longer-horizon model.

Expected expenditures rise with income, age, and family size. Households contribute more than half of their expected expenditures to their accounts. The ratio of average contributions to average expected expenditures is 61.9 percent for the younger and 54.9 percent for older households. The last column gives an expected difference of expenditures with a HSA and with a traditional group plan. Expected utilization is lower with HSAs for all deciles and for both younger and older households. Note that the increase is monotonic for the younger group but is not for the older group. For the younger group, the decline represents 9.90 percent reduction relative to group expenditures for the younger group and a 6.3 percent reduction for older households. The theoretical effect of HSA enrollment on total health care expenditures is not obvious. A higher deductible will reduce utilization, but this is softened somewhat by the tax-preferred account. The overall effect will depend on the level of account balances actually chosen. If a household mistakenly chose an excessively-high contribution level, the incentive to spend today on health care increases either because (as in our model) unused balances can only be consumed after paying taxes and a penalty or (in general) usage of unused balances must wait until a future period. The simulation, which computes optimal HSA contributions and balances, provides support for the claim that HSAs will significantly reduce the level of health care utilization.

6.3 Discussion

In the preceding results we find evidence of both adverse and favorable selection into HSA plans, though in no case was the effect large. Why do we fail to find the death spiral in these preliminary results? There are a number of possible explanations, some of which are related to modeling assumptions. HSAs are modeled as being similar to the traditional Group coverage alternative. We believe the HSA characteristics chosen are fairly typical. However, it may be that selection would be more pronounced for firms with high-coverage traditional plans. Another concern is that HSAs might also be setup with more exclusions for specific medical conditions. Since we have not tried to disaggregate medical expenditures into categories, we cannot address this in the current version of the paper. On the other hand, such exclusions are often a feature of traditional plans and have little to do with HSAs in particular.

Second, we have used a proportional employer subsidy instead of a fixed-dollar subsidy. Since

HSA premia are so much lower, adverse selection in firms with fixed dollar subsidies would likely be more severe. For example, using the numbers in Table 4 we observe that the Group premium is $4,600 and and the HSA premium is $2,200. Proportional 50 percent subsidies cut these to $2,300 and $1,100, so that the Group plan is about twice the price of the HSA. If, instead, the employer offered a $1,500 fixed subsidy, the employee costs (ignoring taxes) would be $3,100 and $700, and adverse selection would likely increase.

As seen above, the specifics of the pool composition do affect the equilibrium. Even if a typical firm experiences limited adverse selection that does not imply all firms are safe. In addition, the variation in risk from age, income decile, family size cells may not be sufficient to tease out significant selection effects. We can address this by adding additional demographics. Alternatively, we could introduce true asymmetric information by assuming that each cell is composed of a mixture of healthy and sick households. With group premiums, all heterogeneity is treated as asymmetric information, even though the household risk types are in fact observable. The mixture distribution would allow us to vary the amount variation in risk types within cells.

Finally, the conventional wisdom about HSAs and FSAs is sometimes wrong. For example, Cardon (2009) shows that Flexible Spending Accounts can strengthen insurance pools. It is tempting to notice a high deductible and a lower premium and conclude that HSAs are simply a low coverage alternative. However, both the theoretical model and simulation results suggest that the reality is more complex. The ability to self-insure through the saving account reduces the effect of the deductible. Risk types matter, of course, but it is also true that income and tax effects seem to be important. The complexities of HSA plans (dynamics, corner solutions, kinks, etc.) make these plans more difficult to evaluate.

7 Conclusion

This work is very preliminary, but we believe it is promising. The approach we have taken highlights subtle economic effects that can easily be missed in alternative models. Our results suggest that properly-designed HSAs are potentially a useful option for many households, and carry the potential to reduce (modestly) the ranks of the uninsured. Perhaps surprisingly, we find little evidence of adverse selection. More work is needed to identify potential cases where selection may be problematic. Plan design is important, as usual.

Although our primary purpose is to estimate the effect of various proposals on the number of uninsured, our framework is sufficiently flexible to handle a variety of simulation tasks. For example, our framework estimates health expenditures jointly with insurance choice. It would also be possible to estimate standard economic welfare effects, quantifying the gains and losses to various policies measured in terms of consumer surplus. Additional micro-level simulations concerning firm choice of optimal policies for various demographic compositions of employees are also feasible within this framework.

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Table 1: Method of Moments Estimation

Theoretical Moments				
$E(X^*) = \frac{Y+KE(\theta)}{K+\alpha}$				
$Var(X^*) = (\frac{K}{K+\alpha})^2 Var(\theta)$				
$\varepsilon_p = \frac{\alpha\left((\alpha E(\theta)-I)\frac{dK}{d\alpha} - (I+KE(\theta))\right)}{(K+\alpha)(I+KE(\theta))}$				
$\varepsilon_I = \frac{I}{K+KE(\theta)}$				
Sample Moments				
RAND HIE Estimates				
$\widehat{\varepsilon}_p^R$	-0.15			
$\widehat{\varepsilon}_I^R$	0.2			
			Age< 40	
Family Size	$\overline{X}$	S	$\widehat{p}$	
1	2.6478	7.7729	0.3798	
2	4.4176	8.7298	0.0535	
3	5.3495	8.3094	0.0317	
4	6.5910	12.1283	0.0312	
> 4	6.8319	10.9560	0.0241	
			Age $\geq$ 40	
Family Size	$\overline{X}$	S	$\widehat{p}$	
1	7.8235	14.9325	0.1578	
2	10.4103	15.9165	0.0358	
3	9.1954	15.9990	0.0346	
4	8.5338	12.5475	0.0216	
> 4	8.6598	16.5576	0.0248	
Estimates				
			Age < 40	
Family Size	$\widehat{\mu}$	$\widehat{\sigma}$	$\widehat{\lambda}$	$\widehat{\gamma}$
1	2.1530	7.7931	0.0005	-0.3386
2	3.6007	8.7676	0.0010	-0.3422
3	4.3657	8.3531	0.0013	-0.3442
4	5.3878	12.2070	0.0017	-0.3468
> 4	5.5866	11.0298	0.0018	-0.3473
			Age $\geq$ 40	
1	6.3849	15.0113	0.0013	-0.3442
2	8.5163	16.0287	0.0019	-0.3480
3	7.5140	16.0985	0.0016	-0.3462
4	6.9691	12.6199	0.0015	-0.3452
> 4	7.0729	16.6545	0.0015	-0.3454

Notes: $X^* = \frac{Y+K\theta}{K+\alpha}$, where Y is income and $K = (\frac{\gamma}{\alpha})^{1-\lambda}$.
$\theta \sim Lognormal(\mu, \sigma^2)$
$\widehat{\varepsilon}_p^R$ and $\widehat{\varepsilon}_I^R$ are estimates from the RAND Health Insurance Experiment.
$U(C,H) = \frac{C^\lambda - 1}{\lambda} + \gamma\frac{(X-\theta)^\lambda - 1}{\lambda}$

Table 2--Market Share Estimates--Individual Market
Multinomial Probit Estimates

	No HSA			HSA Available					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)		
Under 40 Years	Uninsured	Public	Non-Group	Uninsured	Public	Non-Group	HSA	HSA Share	HSA/NG
Income Decile									
1	0.5343	0.4214	0.0443	0.5202	0.4029	0.0363	0.0405	0.5273	1.1154
2	0.4842	0.4684	0.0474	0.4709	0.4466	0.0393	0.0432	0.5240	1.1007
3	0.6635	0.2771	0.0593	0.6428	0.2570	0.0484	0.0519	0.5175	1.0727
4	0.7165	0.2117	0.0718	0.6901	0.1915	0.0579	0.0606	0.5114	1.0467
5	0.7394	0.1504	0.1102	0.6998	0.1277	0.0858	0.0866	0.5024	1.0096
6	0.7362	0.1309	0.1328	0.6898	0.1075	0.1017	0.1010	0.4985	0.9939
7	0.6944	0.1462	0.1594	0.6425	0.1175	0.1204	0.1197	0.4985	0.9942
8	0.7318	0.0939	0.1743	0.6720	0.0718	0.1294	0.1269	0.4952	0.9808
9	0.6098	0.1258	0.2644	0.5364	0.0905	0.1875	0.1856	0.4975	0.9900
10	0.4419	0.1189	0.4392	0.3552	0.0730	0.2873	0.2845	0.4975	0.9902
Average	0.6352	0.2145	0.1503	0.5920	0.1886	0.1094	0.1101	0.5015	1.0061
40+ Years									
Income Decile	Uninsured	Public	Non-Group	Uninsured	Public	Non-Group	HSA	HSA Share	HSA/NG
1	0.4234	0.5570	0.0196	0.4179	0.5444	0.0164	0.0213	0.5643	1.2953
2	0.3069	0.6639	0.0292	0.3006	0.6455	0.0250	0.0289	0.5360	1.1553
3	0.5299	0.4214	0.0487	0.5160	0.3989	0.0407	0.0444	0.5219	1.0917
4	0.6004	0.3350	0.0646	0.5800	0.3103	0.0530	0.0566	0.5163	1.0675
5	0.6571	0.2358	0.1071	0.6221	0.2061	0.0846	0.0872	0.5075	1.0304
6	0.6678	0.2007	0.1315	0.6252	0.1698	0.1017	0.1033	0.5039	1.0157
7	0.6371	0.2063	0.1565	0.5893	0.1709	0.1192	0.1206	0.5029	1.0119
8	0.6993	0.1292	0.1715	0.6431	0.1016	0.1282	0.1272	0.4981	0.9923
9	0.5779	0.1651	0.2570	0.5097	0.1230	0.1838	0.1834	0.4995	0.9980
10	0.4318	0.1266	0.4416	0.3461	0.0760	0.2904	0.2875	0.4975	0.9899
Average	0.5532	0.3041	0.1427	0.5150	0.2746	0.1043	0.1060	0.5041	1.0166

Notes: Estimates from multinomial probit regression. Model includes utility and dummies for income decile, family size, and educational attainment. Unit of observation is a household as defined in the MEPS.

Table 3—Market Share Estimates—Group Market
Multinomial Probit Estimates

	No HSA				HSA Available						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Under 40 Years	Uninsured	Public	Non-Group	Group	Uninsured	Public	Non-Group	Group	Group HSA	HSA Share	HSA/Group
Income Decile											
1	0.1190	0.0667	0.0294	0.7849	0.0785	0.0337	0.0114	0.5045	0.3719	0.4190	0.7373
2	0.2800	0.1408	0.0324	0.5468	0.2186	0.0878	0.0157	0.3727	0.3051	0.4501	0.8187
3	0.2406	0.0936	0.0325	0.6333	0.1736	0.0476	0.0139	0.4033	0.3616	0.4728	0.8967
4	0.1982	0.0637	0.0180	0.7201	0.1321	0.0270	0.0064	0.4331	0.4014	0.4810	0.9268
5	0.1525	0.0291	0.0116	0.8068	0.0924	0.0093	0.0035	0.4609	0.4339	0.4849	0.9415
6	0.1093	0.0211	0.0107	0.8588	0.0605	0.0059	0.0029	0.4768	0.4538	0.4876	0.9517
7	0.0863	0.0145	0.0099	0.8893	0.0448	0.0035	0.0024	0.4839	0.4654	0.4903	0.9619
8	0.0641	0.0133	0.0113	0.9113	0.0312	0.0030	0.0027	0.4893	0.4738	0.4919	0.9683
9	0.0305	0.0140	0.0053	0.9503	0.0127	0.0029	0.0010	0.4987	0.4847	0.4929	0.9720
10	0.0315	0.0147	0.0070	0.9469	0.0133	0.0031	0.0014	0.4974	0.4848	0.4936	0.9746
Average	0.1312	0.0472	0.0168	0.8048	0.0858	0.0224	0.0061	0.4620	0.4236	0.4783	0.9169
40+ Years											
Income Decile	Uninsured	Public	Non-Group	Group	Uninsured	Public	Non-Group	Group	Group HSA	HSA Share	HSA/Group
1	0.0851	0.0708	0.0172	0.8269	0.0537	0.0332	0.0068	0.5481	0.3582	0.3952	0.6534
2	0.1588	0.0765	0.0217	0.7430	0.1049	0.0334	0.0082	0.4618	0.3916	0.4589	0.8481
3	0.1529	0.0576	0.0225	0.7670	0.0968	0.0221	0.0079	0.4567	0.4165	0.4770	0.9121
4	0.1233	0.0368	0.0114	0.8285	0.0717	0.0117	0.0034	0.4719	0.4412	0.4832	0.9349
5	0.0995	0.0175	0.0076	0.8754	0.0534	0.0044	0.0020	0.4828	0.4575	0.4866	0.9476
6	0.0721	0.0132	0.0071	0.9075	0.0359	0.0029	0.0016	0.4898	0.4698	0.4896	0.9592
7	0.0597	0.0095	0.0069	0.9239	0.0284	0.0019	0.0015	0.4933	0.4749	0.4905	0.9628
8	0.0467	0.0095	0.0083	0.9356	0.0211	0.0019	0.0017	0.4956	0.4797	0.4919	0.9681
9	0.0215	0.0101	0.0040	0.9644	0.0083	0.0019	0.0006	0.5013	0.4879	0.4932	0.9733
10	0.0271	0.0114	0.0052	0.9563	0.0109	0.0022	0.0009	0.4990	0.4869	0.4939	0.9758
Average	0.0847	0.0313	0.0112	0.8728	0.0485	0.0116	0.0035	0.4900	0.4464	0.4767	0.9110

Notes: Estimates from multinomial probit regression. Model includes utility and dummies for income decile, family size, and educational attainment. Unit of observation is a household as defined in the MEPS.

Table 4: Simulation of HSA Introduction into Group Pool
50% Employer Contribution, Uniform Distribution of Employees

Under 40 Years

Income Decile	Uninsured	Public	Group	Uninsured	Public	Group	HSA	HSA Share	HSA/Group
1	0.1669	0.0583	0.7749	0.0985	0.0183	0.414	0.4693	0.5313	1.1336
2	0.3067	0.1392	0.5541	0.2224	0.073	0.3337	0.3709	0.5264	1.1115
3	0.2333	0.0824	0.6843	0.164	0.0331	0.3997	0.4032	0.5022	1.0088
4	0.1744	0.053	0.7725	0.114	0.0158	0.4406	0.4296	0.4937	0.9750
5	0.1275	0.0198	0.8526	0.0657	0.0026	0.4705	0.4612	0.4950	0.9802
6	0.0887	0.0112	0.9001	0.0426	0.0004	0.4846	0.4724	0.4936	0.9748
7	0.0706	0.0065	0.923	0.0289	0	0.4906	0.4805	0.4948	0.9794
8	0.0497	0.0063	0.944	0.0211	0	0.4959	0.483	0.4934	0.9740
9	0.0183	0.0086	0.9731	0.0083	0	0.5042	0.4875	0.4916	0.9669
10	0.0185	0.0089	0.9726	0.0094	0	0.504	0.4866	0.4912	0.9655
Average	0.125	0.039	0.835	0.077	0.014	0.454	0.454	0.5004	1.0014

40+ Years

Income Decile	Uninsured	Public	Group	Uninsured	Public	Group	HSA	HSA Share	HSA/Group
1	0.0868	0.0737	0.8395	0.052	0.0335	0.5443	0.3702	0.4048	0.6801
2	0.1423	0.0596	0.7981	0.0871	0.0201	0.4733	0.4195	0.4699	0.8863
3	0.1345	0.0405	0.825	0.0744	0.0106	0.4754	0.4395	0.4804	0.9245
4	0.1064	0.023	0.8706	0.0569	0.0034	0.482	0.4577	0.4871	0.9496
5	0.0839	0.0072	0.9088	0.0385	0	0.4909	0.4706	0.4894	0.9586
6	0.0569	0.0053	0.9378	0.0246	0	0.4971	0.4783	0.4904	0.9622
7	0.0477	0.0039	0.9484	0.0198	0	0.4976	0.4827	0.4924	0.9701
8	0.0308	0.0046	0.9646	0.0135	0	0.5016	0.4849	0.4915	0.9667
9	0.0149	0.005	0.9801	0.0045	0	0.5059	0.4896	0.4918	0.9678
10	0.0167	0.0069	0.9764	0.0066	0	0.5054	0.488	0.4912	0.9656
Average	0.072	0.023	0.905	0.038	0.007	0.497	0.458	0.4795	0.9211
Premium			$5,319			$5,286	$2,714		

Table 5: Simulation of HSA Introduction into Group Pool

50% Employer Contribution, Non-Uniform Distribution of Employees

Under 40 Years

Income Decile	Uninsured	Public	Group	Uninsured	Public	Group	HSA	HSA Share	HSA/Group
1	0.1799	0.0701	0.75	0.1057	0.0242	0.3926	0.4775	0.5488	1.2163
2	0.3191	0.1521	0.5287	0.2315	0.0782	0.3195	0.3708	0.5372	1.1606
3	0.2386	0.0869	0.6746	0.1675	0.0356	0.3919	0.4049	0.5082	1.0332
4	0.1783	0.0557	0.766	0.1166	0.0166	0.4367	0.4301	0.4962	0.9849
5									
6									
7									
8									
9									
10									
Average	0.229	0.091	0.680	0.155	0.039	0.385	0.421	0.5221	1.0926

40+ Years

Income Decile	Uninsured	Public	Group	Uninsured	Public	Group	HSA	HSA Share	HSA/Group
1	0.0944	0.0886	0.817	0.0565	0.0422	0.5281	0.3732	0.4141	0.7067
2	0.1454	0.0634	0.7912	0.0892	0.0224	0.4669	0.4215	0.4744	0.9028
3	0.1357	0.0425	0.8218	0.0769	0.0111	0.4728	0.4392	0.4816	0.9289
4	0.1077	0.0237	0.8687	0.0571	0.0034	0.4809	0.4585	0.4881	0.9534
5	0.0844	0.0075	0.9081	0.0386	0	0.4898	0.4716	0.4905	0.9628
6	0.0575	0.0053	0.9371	0.0249	0	0.4962	0.479	0.4912	0.9653
7	0.0481	0.004	0.9479	0.0199	0	0.4971	0.4829	0.4928	0.9714
8	0.0309	0.0046	0.9645	0.0135	0	0.5014	0.4851	0.4917	0.9675
9	0.0149	0.005	0.9801	0.0045	0	0.5059	0.4896	0.4918	0.9678
10	0.0167	0.0069	0.9764	0.0066	0	0.5054	0.488	0.4912	0.9656
Average	0.074	0.025	0.901	0.039	0.008	0.494	0.459	0.4813	0.9280
Premium			$6,087			$6,014	$3,193		

Table 6: Simulation of HSA Introduction into Group Pool
50% Employer Contribution, Non-Uniform Distribution of Employees

Under 40 Years

Income Decile	Uninsured	Public	Group	Uninsured	Public	Group	HSA	HSA Share	HSA/Group
1	0.1335	0.0358	0.8307	0.0737	0.0093	0.4618	0.4552	0.4964	0.9857
2	0.2785	0.1138	0.6077	0.1988	0.0549	0.3745	0.3719	0.4983	0.9931
3	0.2204	0.0728	0.7067	0.1529	0.0291	0.4185	0.3995	0.4884	0.9546
4	0.1655	0.0477	0.7868	0.1079	0.0135	0.4516	0.427	0.4860	0.9455
5	0.124	0.0174	0.8586	0.0635	0.0023	0.4762	0.458	0.4903	0.9618
6	0.0862	0.0102	0.9036	0.0412	0.0002	0.489	0.4696	0.4899	0.9603
7	0.0688	0.0061	0.9251	0.0281	0	0.493	0.4789	0.4927	0.9714
8	0.0493	0.0063	0.9444	0.0208	0	0.4981	0.4811	0.4913	0.9659
9	0.018	0.0083	0.9737	0.0082	0	0.5047	0.4871	0.4911	0.9651
10	0.0185	0.0089	0.9726	0.0092	0	0.5044	0.4865	0.4910	0.9645
Average	0.116	0.033	0.851	0.070	0.011	0.467	0.451	0.4915	0.9664

40+ Years

Income Decile	Uninsured	Public	Group	Uninsured	Public	Group	HSA	HSA Share	HSA/Group
1	0.0696	0.0476	0.8828	0.0403	0.0181	0.5778	0.3639	0.3864	0.6298
2	0.1318	0.052	0.8162	0.0768	0.0169	0.4851	0.4212	0.4647	0.8683
3	0.129	0.037	0.834	0.0719	0.0095	0.4813	0.4373	0.4761	0.9086
4	0.1041	0.0216	0.8743	0.0557	0.0033	0.4867	0.4544	0.4828	0.9336
5									
6									
7									
8									
9									
10									
Average	0.109	0.040	0.852	0.061	0.012	0.508	0.419	0.4522	0.8256
Premium			$3,237			$3,246	$1,481		

Table 7: HSA Usage and Health Care Utilization

Estimates from Table 4 Model

Under 40 Years

Income Decile	Z_2	$E(W_2)$	HSA $E(X_2)$	HSA $E(X_2)$-Group $E(X_2)$
1	11.15	11.15	1,480.48	-71.67
2	9.60	9.60	1,663.44	-76.03
3	957.15	681.35	1,927.35	-102.72
4	1,101.84	824.11	2,246.45	-143.27
5	1,712.00	1,083.80	2,517.68	-203.51
6	1,894.32	1,357.41	2,974.78	-290.46
7	2,087.68	1,536.88	3,321.65	-402.98
8	2,450.80	1,827.55	3,802.35	-552.40
9	3,877.21	2,631.02	4,380.11	-616.31
10	4,256.92	3,230.65	5,325.85	-795.59
Average	1,835.87	1,319.35	2,964.01	-325.50

40+ Years

Income Decile	Z_2	$E(W_2)$	HSA $E(X_2)$	HSA $E(X_2)$-Group $E(X_2)$
1	18.85	18.85	4,819.88	-330.28
2	2,747.98	1,940.20	5,078.87	-239.95
3	2,687.26	2,007.78	5,488.23	-293.51
4	3,427.16	2,463.97	5,860.67	-358.95
5	3,323.96	2,490.20	6,051.14	-482.89
6	3,466.94	2,693.36	6,547.99	-569.54
7	3,798.32	2,953.46	6,897.78	-637.95
8	5,546.43	4,204.46	7,778.84	-560.15
9	5,727.10	4,708.78	8,595.39	-601.97
10	6,006.73	5,415.48	9,763.99	-436.72
Average	3,675.07	2,889.65	6,688.28	-451.19

Appendix: Simulation Data and Parameters.

	Decile	Income
Younger	1	$10,000
	2	$12,950
	3	$19,800
	4	$26,010
	5	$34,000
	6	$43,060
	7	$55,050
	8	$70,020
	9	$95,728
	10	$144,992
Older	1	$12,040
	2	$23,000
	3	$33,333
	4	$45,000
	5	$55,305
	6	$68,000
	7	$82,500
	8	$102,049
	9	$141,496
	10	$188,620

Simulation Parameters

Parameter	**Table 2**	**Table 3**	**Table 4**	**Table 5**	**Table 6**	**Table 7**
Group/Non-Group coins, α	0.2	0.2	0.2	0.2	0.2	0.2
Group/Non-Group Deductible, D	500	500	500	500	500	500
HSA coinsurance, α	0.3	0.3	0.3	0.3	0.3	0.3
HSA Deductible, D	3,000	3,000	3,000	3,000	3,000	3,000
Employer share of Premium	0.5	0.5	0.5	0.5	0.5	0.5
Loading factor, Non-group	0.4	0.4	0.4	0.4	0.4	0.4
Loading factor, Non-group HSA	0.4	0.4	0.4	0.4	0.4	0.4
Loading factor, Non-Group	0.4	0.4	0.4	0.4	0.4	0.4
Loading factor, Group	0.18	0.18	0.18	0.18	0.18	0.18
Loading factor, Group HSA	0.18	0.18	0.18	0.18	0.18	0.18
Discount Factor, β	0.9	0.9	0.9	0.9	0.9	0.9
HSA account interest rate, r	0.05	0.05	0.05	0.05	0.05	0.05

Correlation Matrix for Multivariate Normal Errors, a_{ij}

	NoIns	Pub, NO	NG, NO	Pub, O	NG, O	Group	NG HSA	G HSA
No Insurance	1							
Public, Not Offered	0.5	1						
Non-Group, Not Offered	0.5	0.5	1					
Public, Offered	0.5	0.5	0.5	1				
Non-Group Offered	0.5	0.5	0.5	0.5	1			
Group	0.5	0.5	0.5	0.5	0.5	1		
Non-Group HSA	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*	*1*	
Group HSA	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*	*1*

Italicized entries in rows 7-8 and columns 7-8 are augmented for Non-Group and Group HSA.

Coefficient Estimates from Multinomial Probit Model

	Variable	Estimate	Standard Error
	U No Ins	1.9974	0.2535
	U Public, Not Offered	3.8677	0.2719
	U Public, Offered	2.6103	0.3353
	U Non-group, Not offered	2.7382	0.2625
	U Non-group , Offered	2.7461	0.3784
	U Group	3.6716	0.3201
No Insurance (Base)	--	--	--
Not Offered: Public	HS Degree	0.0775	0.0381
	College Degree	0.3197	0.0532
	Income Decile 2	-0.0844	0.0712
	Income Decile 3	-1.2486	0.1082
	Income Decile 4	-1.7753	0.1379
	Income Decile 5	-2.2582	0.1643
	Income Decile 6	-2.5260	0.1892
	Income Decile 7	-2.5799	0.2110
	Income Decile 8	-3.1037	0.2386
	Income Decile 9	-2.9390	0.2690
	Income Decile 10	-2.8625	0.2916
	Family Size	0.1511	0.0157
	Constant	-6.8282	0.4320
Not Offered: Non-Group	HS Degree	0.5450	0.0611
	College Degree	0.9852	0.0708
	Income Decile 2	-0.0292	0.0940
	Income Decile 3	-0.5704	0.1494
	Income Decile 4	-0.7196	0.1923
	Income Decile 5	-0.6589	0.2289
	Income Decile 6	-0.6423	0.2611
	Income Decile 7	-0.5381	0.2842
	Income Decile 8	-0.6821	0.3093
	Income Decile 9	-0.2926	0.3407
	Income Decile 10	0.2669	0.3606
	Family Size	-0.0933	0.0288
	Constant	-3.8284	0.5277
Offered: Public	HS Degree	0.5106	0.0832
	College Degree	0.6285	0.1011
	Income Decile 2	-0.2981	0.2055
	Income Decile 3	-0.3937	0.2413
	Income Decile 4	-0.4500	0.2748
	Income Decile 5	-0.6127	0.3006
	Income Decile 6	-0.5290	0.3288
	Income Decile 7	-0.5570	0.3572
	Income Decile 8	-0.4349	0.3820
	Income Decile 9	-0.0196	0.4184
	Income Decile 10	-0.1541	0.4477
	Family Size	0.0467	0.0295
	Constant	-2.6624	0.8445
Offered: Non-Group	HS Degree	0.7460	0.1289
	College Degree	1.2996	0.1439
	Income Decile 2	-0.8951	0.2303
	Income Decile 3	-1.0464	0.2881
	Income Decile 4	-1.2551	0.3386
	Income Decile 5	-1.3221	0.3828
	Income Decile 6	-1.1925	0.4207
	Income Decile 7	-1.1386	0.4574
	Income Decile 8	-0.9780	0.4888
	Income Decile 9	-0.8537	0.5339
	Income Decile 10	-0.9684	0.5694
	Family Size	-0.0363	0.0281
	Constant	-2.7658	0.9583
Offered: Group	HS Degree	0.5029	0.0581
	College Degree	0.6913	0.0706
	Income Decile 2	-1.3115	0.1483
	Income Decile 3	-1.5926	0.1763
	Income Decile 4	-1.6112	0.2062
	Income Decile 5	-1.5624	0.2307
	Income Decile 6	-1.4549	0.2540
	Income Decile 7	-1.4442	0.2761
	Income Decile 8	-1.3978	0.2962
	Income Decile 9	-1.0942	0.3272
	Income Decile 10	-1.3895	0.3477
	Family Size	-0.1364	0.0178
	Constant	-3.4091	0.6121
	ρ	0.5051	0.1047

Notes: Homoskedastic, single correlation, ρ.

N=29,273; Log simulated-likelihood = -16465.627