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Ian M. McCarthy
FTI Consulting

Rusty Tchernis
Georgia State University, rtchernis@gsu.edu

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Abstract

There is increasing evidence suggesting that Medicare beneficiaries do not make fully informed decisions when choosing among alternative Medicare health plans. To the extent that deciphering the intricacies of alternative plans consumes time and money, the Medicare health plan market is one in which search costs may play an important role. To account for this, we split beneficiaries into two groups—those who are informed and those who are uninformed. If uninformed, beneficiaries only use a subset of covariates to compute their maximum utilities, and if informed, they use the full set of variables considered. In a Bayesian framework with Markov Chain Monte Carlo (MCMC) methods, we estimate search cost coefficients based on the minimum and maximum statistics of the search cost distribution, incorporating both horizontal differentiation and information heterogeneities across eligibles. Our results suggest that, conditional on being uninformed, older, higher income beneficiaries with lower self-reported health status are more likely to utilize easier access to information.

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[*]FTI Consulting, Dallas, TX, USA
[†]Georgia State University
[‡]Correspondence to: Rusty Tchernis, Department of Economics, Andrew Young School of Policy Studies Georgia State University, P.O. Box 3992, Atlanta, GA 30302-3992, U.S.A. E-mail: rtchernis@gsu.edu

1 Introduction

When first established in 1997, the Medicare + Choice (M+C) program aimed to provide beneficiaries alternatives to the standard Medicare Fee-for-Service (FFS) plans. Now termed Medicare Advantage (MA) plans, these provide at a minimum the same coverage offered by standard Medicare FFS and often provide much more, but additional health plan benefits also complicate each beneficiary's choice. In shear number, the choice may be daunting. In 2002, private insurance companies received 174 Center for Medicare and Medicaid Services (CMS) contracts to provide 452 different Medicare health plans for different areas across the US. Some beneficiaries had over 60 different plans offered in their area. Plans can also offer a variety of optional benefits, and although not all plans are available to all beneficiaries, it is clear that the potential choice set is overwhelming for most people. In a study commissioned by AARP, Hibbard and Jewett (1998) find that most beneficiaries do not fully understand the differences between the standard Medicare FFS and M+C plans. More recently, Atherly (2001), Frank (2004) and Heiss, McFadden and Winter (2006), among others, present strong survey evidence suggesting that the choice set is overly complicated and that beneficiaries often do not make fully informed decisions.

We account for these informational problems by adopting a consumer search model. With data on Medicare plan choice, beneficiary information structure and demographic variables, we split buyers into groups of informed and uninformed. If uninformed, beneficiaries only use a subset of covariates to compute their maximum utilities, and if informed, they use the full set of variables considered. Intuitively, we can treat all beneficiaries as being initially uninformed, and through costly search, they can gain knowledge of other characteristics; however, since eligibles have different search costs, not all beneficiaries want to search. This search process is similar to Sorensen (2001), who studies search costs in the market for prescription drugs. Due primarily to data limitations, however, he cannot study the effect of demographic variables on search costs, while in our paper, we parameterize search costs and explicitly estimate search cost coefficients based on the minimum and maximum statistics of the search cost distribution. The main focus of this paper is to explain the primary determinants of these critical search cost values. We estimate this model in a Bayesian framework with Markov Chain Monte Carlo (MCMC) methods, incorporating both horizontal differentiation and information heterogeneities across eligibles.

Our analysis provides two major contributions. One, we embed a heterogeneous search process in a discrete choice model with taste differences. This provides a rich decision process with multiple forms of buyer heterogeneity. And two, we determine not just how beneficiaries gain information (as in the standard reduced form models) but also which types of beneficiaries are closer to making informed decisions than others. Since informed decisions are welfare improving, understanding beneficiary information structure and which beneficiaries are closer to making an informed decision has important welfare implications. Intuitively, imagine we want to assess our favorite sports team's performance. We might first look at wins and losses, which is what the standard reduced form models tell us about a beneficiary's information structure—are beneficiaries informed or uninformed and what factors have the most influence? But there are degrees of winning and losing, and knowing whether our team lost by 1 or 100 points makes a difference. Our search model, in some sense, tells us the score. Specifically, if we consider a search cost cutoff above which people are uninformed and below which are informed, we find that higher income beneficiaries are most likely closer to the cutoff than lower income beneficiaries, while beneficiaries with more assistance are more likely to have search costs well away from the cutoff. These results provide strong insight into who would most benefit from easier access to information and allow us to determine, of those that are uninformed, who needs the least help to make an informed decision. Therefore, with regard to beneficiary information structure, we can *ex ante* assess the efficiency of proposed welfare improving processes.

Search is certainly not the only avenue by which beneficiaries simplify their choice sets. Gilbride and Allenby (2006), for example, develop a screening-rule model where beneficiaries choose plans essentially in two stages. In stage one, they select a subset of plans based on a screening rule, and in stage two, they choose the best plan in their new information set. They apply this model to self-reported survey data. Li (2006) extends this by incorporating demographic variables and devoting more attention to the development of the screening rule mechanism. She also applies her model to realized choices rather than survey data of hypothetical choices.

While both papers are important steps in developing more realistic choice models when decisions are complicated, the underlying motivation for the screening rule is somewhat disconcerting. This assumes that people cannot fully understand the intricacies of each choice and are burdened by "information overload." To ease their decision, they screen their choices and only look at some subset. In a search model, however, anyone *can* understand the options available to them, but the cost of doing so may be substantial. The screening model also does not differentiate between informed and uninformed buyers and, as such, cannot address which types of buyers might be closer to making informed decisions than others.

Moreover, in the Medicare health plan market, there is strong evidence that search may play a role. First, there does seem to be some distinction between informed and uninformed beneficiaries. When asked a series of questions regarding how intensively they tried to find plan information, over half of our sample indicated making essentially no effort. Such beneficiaries could not have made an informed decision—even if the decision were somewhat simplified by a screening rule, they would still have to research whatever plans passed the first-stage screening process. Second, there are significant differences across plans offered to each beneficiary, creating a strong benefit for those beneficiaries deciding to actively research several different plans. For instance, the average difference between the lowest and highest premium plans offered in a beneficiary's area is over \$100. Similarly large differences exist for inpatient hospital care costs (\$20.11), doctor and specialist co-pay (\$13.32), and several services such as vision and hearing. Third, as mentioned previously, many beneficiaries cite a strong lack of understanding with their plan's benefits, implying that they could not have thoroughly researched some of their plan's attributes.

The remainder of the paper is organized as follows. In Section 2, we briefly describe the history of the Medicare Advantage program, Section 3 explains the basic search theory, Section 4 explains the data, Section 5 sets up the model, Section 6 explains the estimation process and Section 7 summarizes the results. The Gibbs sampler algorithm and simulation results are deferred to the Appendix.

2 Medicare History

Established in 1965, Medicare provides baseline medical coverage to individuals 65 years or older or those with permanent disabilities. Until 1982, the only option for Medicare beneficiaries was the basic Medicare Fee-for-Service (FFS), which consists of two parts. All eligibles are automatically enrolled in Part A, which covers hospital stays and skilled nursing facility care, and in 2002, roughly 95% of beneficiaries also paid for Medicare Part B, the voluntary supplemental program covering physician services, medical equipment, and most outpatient hospital services. Most beneficiaries have already paid for Part A through payroll taxes, while

Part B usually requires an additional premium ($54 in 2002 and $96.40 in 2007). Since 2006, beneficiaries can also receive prescription drug coverage through private drug plans (Medicare part D).

Since the Balanced Budget Act of 1997, and revised in 2003 by the Medicare Modernization Act, beneficiaries can enroll in private health insurance plans called Medicare + Choice (M+C) plans. These plans are provided by private companies who contract with the Center for Medicare and Medicaid Services (CMS) yearly and are designed to replace the traditional Medicare FFS plans. Contracts apply at the county level, and there can be multiple plans provided under each contract. Since contracts are county specific, only those residents living in the county in which the contract applies have access to the plans under that contract.

There are two different types of plans under the M+C heading–risk plans (e.g., Managed Care plans—mainly Health Maintenance Organizations (HMOs), Preferred Provider Organization plans, Provider-Sponsored Organization plans and Private Fee-for-Service plans) and cost plans. Risk and cost plans differ in that CMS provides a monthly payment to risk plans for each enrolled beneficiary, while with cost plans, CMS only pays the cost of services in excess of the standard Medicare FFS. Prior to the Medicare Modernization Act, however, most M+C plans were Managed Care plans.[1]

In choosing their Medicare health plans, beneficiaries give up the traditional benefits of Medicare FFS but must still enroll in Parts A and B. CMS also requires M+C plans to offer at least what the beneficiary could receive from Medicare FFS. For 2002 coverage, open enrollment was from November 1 to December 31, 2001. During this time, eligibles ages 65 years or older without end stage renal disease (ESRD) could choose any plan available in their area. Limited enrollment went from January 1 through June 30, 2002, where beneficiaries could still enroll in M+C plans but only if the plan in question was accepting new members.[2] During the limited enrollment period, beneficiaries were free to switch plans but could only do so once. This included switching back to the standard Medicare FFS. For example, a beneficiary could enroll in November of 2001 and switch plans in May of 2002, at which point they were locked-in to the new plan for the rest of the year. Beneficiaries might also move out of their plan's service area, in which case they could still receive coverage if the plan allows, or they must disenroll

[1]Other types of health plans exist, such as Health Care Prepayment Plans, but are strongly regulated by CMS. For a detailed description of different types of plans, see the "Medicare & You" booklet published yearly by CMS or "Report to the Congress: Medicare Payment Policy" from MedPAC.

[2]Beneficiaries were generally only denied membership if the plan had previously set a maximum member number and had already reached that limit.

and choose another plan in their new location or stay with Medicare FFS.

Since 2004, M+C plans have changed to Medicare Advantage (MA) plans. Similar to M+C, private companies provide these plans with contracts from CMS. The types of plans include Health Maintenance Organizations, Preferred Provider Organization plans, Private Fee-for-Service plans, and Medical Savings Account plans. New plans include Regional Preferred Provider Organization plans and Special Needs Plans. Any plans besides Private FFS and Medicare Savings Accounts must offer at least one benefit package that includes prescription drug coverage.

For the most part, standard Medicare FFS leaves the beneficiary with a large amount of risk, often without dental, vision, long-term care, preventative care, or prescription drug coverage. Parts A and B also require rather substantial deductables and co-payments and do not place a maximum on out-of-pocket expenses. Due to this increased exposure, nearly 90% of beneficiaries have some sort of supplemental coverage, either through Medicaid, Medigap, employer provided insurance, or Medicare Advantage. For those enrolled in MA plans, they must pay the plan premium and also enroll in Medicare part B and pay the part B premium. Despite the extra premium, most MA plans offer significantly more benefits than the standard Medicare FFS. In fact, in our dataset, 33% of MA plans charge no additional premium and still offer more benefits.[3]

3 Literature Review

Due to the influx of Medicare beneficiaries, there has been increased attention paid to the Medicare Advantage market. This includes analyzing the enrollment decision process, the utilization process, as well as the overall welfare effects of privately provided Medicare health plans. Despite the increased awareness and applicability, there is no consensus as to how beneficiaries actually make their enrollment decisions. Initial studies, such as Atherly et al. (2004) and Dowd et al. (2003), model this decision in a standard discrete choice framework (e.g., probit). But due to strong evidence suggesting that beneficiaries do not make informed decisions, the complete information assumption inherent in the standard discrete choice models has come under question. Some attempts to address these problems include Frank and Lamirand (2007), Gillbride and Allenby (2006), Lowenstein (1999) and Li (2006), all of which integrate concepts

[3]We treat Medicare Advantage and Medicare + Choice interchangeably, even though our 2002 data technically only apply to the Medicare + Choice market.

from behavioral psychology (e.g., information overload or anxiety) into consumer decision processes. Li (2006), however, is the only paper to use observational data rather than experimental or hypothetical survey data.

Although not strictly related to behavioral psychology, the motivation for our approach is similar. We acknowledge that beneficiaries are often not fully informed of all characteristics across all possible decisions; however, contrary to the approaches above, we believe that all beneficiaries are capable of being completely informed. The assumed computational capacity of beneficiaries is an important difference between the screening and search models. In a search context, the problem is that each person has a different cost of collecting information and therefore may not make an informed decision.

3.1 Search Literature

Theoretically, consumer search first developed as an explanation for observed price differences in seemingly homogeneous product markets. For instance, assume that several buyers are all looking for the best price for some homogeneous good sold by several firms.[4] Everyone knows the distribution of prices but not the specific price of a given firm. If each buyer has some cost of going from one firm to another, and this cost is different across buyers, then under certain restrictions on the search cost and price distributions, there exists a price dispersed equilibrium.[5] Using this theoretical background, Hong and Shum (2006) impose the equilibrium restrictions in order to estimate the search cost distribution using only price data. They apply this analysis to the online market for statistics textbooks and show that search may account for the observed price dispersion in this seemingly homogeneous product market.

If we further assume that firms have some marginal cost differences, then price dispersed equilibria exist under more general search cost distributions.[6] Hortacsu and Syverson (2004) exploit this theoretical setup in their study of search costs and mutual funds. Similar to Hong and Shum (2006), they exploit equilibrium relationships in order to estimate the search cost distribution in the market for S&P 500 index funds using both price and quantity (market share) data. They do so under three general sequential search settings. One, they assume funds are homogeneous and that each fund is equally likely to be sampled, in which case

[4]There are two general branches of search—sequential search and fixed sample size search. We focus here on the sequential consumer search rule. For a survey of both, as well as empirical studies, see Baye, Morgan and Scholten (2006).

[5]See Rob (1985) and Stahl (1989) for more detail.

[6]See Bénabou (1993) and Carlson and McAfee (1983) for more detail.

cutoff search cost values come directly from the equilibrium restrictions of the model. Two, they allow for some vertical product differentiation where plans remain equally likely to be sampled. Here, given some additional marginal cost assumptions, search cost cutoffs are again estimated directly from equilibrium restrictions. And three, they consider homogeneous funds with unequal sampling probabilities, and estimate the parameters of an assumed search cost distribution using nonlinear least squares. This paper is particularly interesting as it integrates consumer search and product differentiation; however, as Hortacsu and Syverson indicate, they cannot consider taste heterogeneities along with search costs since their data do not provide an exogenous source of variation for the search cost distribution.[7]

The main goal in these empirical search models is to estimate the search cost distribution, usually in a structural model and usually in a nearly homogeneous good market, or to more formally model the mechanism by which certain consumers are more informed than others. There is currently little work, however, on the actual determinants of individual consumer search costs. Moreover, the data considered in these models do not allow for both taste differences across choices and heterogeneous search costs. This paper addresses both of these issues.

4 Data

The data for individual plan characteristics come from the Medicare Health Plan Compare (MHPC) dataset. This is a freely available dataset collected by CMS. Since we use 2002 beneficiary demographic data, we use the beginning-of-year MHPC for 2002. We combine the county code data with the benefit structure data to get one dataset consisting of the Medicare plan contract, the plan id, the county code from which this contract operates, and the benefit structure of each plan. The full dataset includes up to 38 different plan attributes for each plan under each contract, where there are 452 different plan/contract combinations and 174 different contracts. Variable definitions and summary statistics are included in Table 1, where we see that nearly 70% of plans offered some sort of hearing, vision or prescription drug coverage, while less than 30% offered any dental coverage. As mentioned previously, we also see the large range of premium, inpatient hospital care costs, skilled nursing facility costs and doctor co-pay. In premium alone, the incentive to search could exceed $300. Since all eligibles have access to

[7] Other empirical search studies include Wildenbeest (2006), which also estimates the search cost distribution with vertically differentiated products, and Moraga-González and Wildenbeest (2006). Lewis (2004) and Sorensen (2001) also study consumer search but do not estimate the search cost distribution.

the standard Medicare FFS, we treat this as the baseline utility that anyone can obtain for free. We normalize the FFS premium to \$0, and we set the inpatient hospital care equal to \$13.53 per day for the first 60 days and the doctor or specialist co-payment to \$25 as per the 2002 "Medicare and You" booklet.

Table 1 goes here

For informed beneficiaries, we consider premium (in excess of the \$54 for Part B coverage), prescription drug coverage, average doctor or specialist co-pay, vision services, dental services, hearing services, home health care coverage, physical exam coverage, inpatient hospital care costs and skilled nursing facility costs. We also combine general health education and acupuncture into one variable named "extras". These characteristics are commonly studied in the Medicare literature. Due to little variability across plans, we do not use out-of-network coverage, chiropractic care or emergency room coverage in our analysis. For uninformed beneficiaries, we assume they only observe premium, doctor and specialist co-pay and prescription drug coverage. These were chosen for two reasons. One, the knowledge and needs supplement indicates that the cost of medical services is the most important aspect to beneficiaries next to general Parts A and B services—premium and co-pay are the most easily observed out-of-pocket cost variables included in our analysis. Two, in the screening literature, there is strong evidence that prescription drug coverage is a major screening variable.[8] For these reasons, we use premium, co-pay and prescription drug coverage as our covariates for uninformed beneficiaries.

We then combine these plan characteristics with individual beneficiary characteristics from the 2002 Medicare Current Beneficiary Survey (MCBS), Access to Care module. This contains demographic data such as age, income, race, self-reported health status and Medicare use, as well as whether the beneficiary is employed or not,[9] as described in Table 2, for a cross-section of 16,409 beneficiaries.

Table 2 goes here

[8] See Li (2006) for more detail.

[9] We note that one's employment status may intuitively impact a beneficiary's search decision. To estimate such effects, we include active workers in our estimation and include a dummy variable for whether a beneficiary is employed or not in our estimation of search cost coefficients.

In order to characterize each beneficiary's plan choice set, we apply the following filters: (1) we exclude beneficiaries with unknown age – 94 observations; (2) we exclude beneficiaries completing interviews in medical facilities (e.g., nursing homes) – 1,173 additional observations; (3) we exclude beneficiaries classified as anything other than "aged, no ESRD" – 2,536 additional observations; (4) due to fundamental differences between, say, the choice of Medigap versus M+C plans, we follow Atherly, Dowd, and Feldman (2004) and exclude beneficiaries with any type of supplemental coverage besides M+C (e.g., Medigap, Medicaid, public health coverage, or employer provided insurance) – 9,499 additional observations; and (5) we exclude beneficiaries claiming to have HMO or GHP coverage but who do not have a contract offered in their area – 218 additional observations.

Using the county code data, we match beneficiaries to a specific plan and choice set. We form the choice set by matching the contracts offered by county code with each beneficiary's county of residence. Matching beneficiaries to specific plans, however, is not as clear. The MCBS only has data on the contract under which the beneficiary's plan exists—not which plan was chosen. Therefore, we match plans to beneficiaries by analyzing the deviation between each plan's characteristics and the beneficiary's perceived plan characteristics.[10] For some beneficiaries, however, this still does not uniquely match them to one plan. In this case, we assume that beneficiaries choose the best plan in regard to premium, prescription drug coverage, co-pay, vision, dental, hearing, physical exam coverage, inpatient hospital care costs and skilled nursing facility costs, in this order.[11] Recall that we consider only the first three characteristics for uninformed eligibles as they are assumed to never see the remaining characteristics. If plans remain identical across these characteristics, we randomly assign one of the remaining plans. We lose another 655 observations who are under contracts that do not match the contracts available to them or who are matched to plans not offered under their original contract.[12] The final dataset therefore consists of $N = 2,234$ beneficiaries, 970 of which are enrolled in the basic Medicare FFS and the remaining enrolled in a Medicare health plan (managed care plan). From Table 2, we see that a large portion of our sample has annual income between \$5,000 and \$25,000, education at or below a high school diploma, good to excellent (self-reported) health

[10]The survey asks questions about how much the beneficiary pays per month and what type of prescription drug coverage they receive. We use the answers to these questions to determine the "distance" from the benefits available to the beneficiary and the benefits received by the beneficiary.

[11]These characteristics are sufficient to match beneficiaries to plans, so we ignore health education and acupuncture in our matching process.

[12]Most of these observations are those who have moved or switched plans throughout the year but who had a plan prior to moving.

status and few chronic diseases.

For data on search behavior, we use the beneficiary Knowledge and Needs survey. These variables explain whether a beneficiary contacted Medicare prior to choosing their plan, whether they accessed the internet, reviewed the plan quality charts, and other similar activities. Summary statistics are included in Table 3. This tells us how active beneficiaries are in finding information, where we see that only 6% claimed to have looked for payment information and only 5% claimed to have looked for benefit information. Over 43%, however, claimed to read and at least partially understand the "Medicare and You" booklet.

Table 3 goes here

To appropriately split beneficiaries into groups of informed and uninformed, we need to determine which avenues a beneficiary can take to gain information. From the data available, we determine 11 such avenues: (1) whether the beneficiary switched plans within the past year, (2-4) whether they are informed of Medicare payment, benefit or coverage information, (5) whether they are informed of HMO information, (6) whether they read the "Medicare and You" booklet, (7-8) whether they looked at quality ratings or the plan information chart, (9) whether they called the Medicare hotline, (10) whether they visited the Medicare website (provided they have internet access), and (11) whether they have someone assisting them in their Medicare decisions. Out of these 11 categories, we see from Table 4 that over 45% of our sample made no observable attempt to gain information.[13] Of the 600 that took only one avenue, most of them read the "Medicare and You" booklet. And since the booklet is fairly general and does not discuss individual plans, we assume that those beneficiaries who only read the booklet still most likely made an uninformed decision. We therefore assume that anyone taking one or less avenue to gain information is uninformed, leaving $N_1 = 627$ informed beneficiaries and $N_2 = 1,607$ uninformed beneficiaries.

Table 4 goes here

[13] The percentages presented in Table 4 are consistent across the subsets of beneficiaries choosing FFS and those choosing HMO coverage.

5 The Model

There are $i = 1, ..., N$ beneficiaries choosing between $j = 1, ..., J_i$ different health care plans, where each beneficiary has some search cost, $c_i > 0$, and where the numbers and types of plans available vary by zip code and county code. As mentioned previously, N is the sum of N_1 informed buyers and N_2 uninformed buyers. All N_2 uninformed beneficiaries know only a subset of plan characteristics as well as the maximum utility available to them if they decide to search, while the N_1 informed beneficiaries have full information on all plan characteristics. This type of information structure is similar to Sorensen (2001), where buyers know the maximum utility available to them but must engage in costly search to match plans with utility values.

Everyone has information on some characteristics but must engage in costly search in order to become fully informed. In this sense, searching and making an informed decision are synonymous. Since utilities and search costs are heterogeneous across beneficiaries, not everyone finds it beneficial to search. Those that do not search therefore choose the best plan based on a subset of characteristics. This subset determines the baseline utility that buyers can attain with certainty and without search. Note that, since some attributes remain unknown without search, uninformed beneficiaries may select plans that, had they been informed, would not have offered the highest utility. The timing of the process is as follows:

1. Buyers form their own benefit of search, b_i, determined by the difference between the maximum utility available to them through search and the maximum available without search.

2. Buyers decide to search or not, depending on their search cost c_i. If $c_i < b_i$, then beneficiary i searches.

3. If beneficiary i is completely informed, they choose the highest utility available. Otherwise, they choose the plan offering the highest utility according to a subset of covariates.

Recall from Section 3 that the standard theoretical search model assumes buyers know the full distribution of utilities available but are *ex ante* uninformed about which plans offer which utilities. In a sequential setting, buyers would go from one plan to the next searching for the best deal and stop searching once the benefit to search is below their cost. The major differences between our “all or nothing” search process and this standard theoretical search process is two-fold. One, in our model, beneficiaries have knowledge of a subset of characteristics across all plans. Therefore, beneficiaries need not search in order to look at more than one plan—they must search in order to look at more characteristics. Two, if they search, they do so exhaustively. Search therefore has two effects on beneficiary behavior and utility: (1) the beneficiary becomes aware of plan attributes that would otherwise have a negative effect on their utility, and thus avoids the plan if such negative effects are sufficiently large; or (2) the beneficiary becomes aware of plan attributes that have a positive effect on their utility and will choose differently (relative to had they been uninformed) if such effects are sufficiently large. In either case, an informed decision yields a higher *ex post* utility than an uninformed decision. In this sense, the search process automatically dictates that an informed decision is no worse, but perhaps better, from a welfare standpoint than an uninformed decision. This is true for all beneficiaries and derives theoretically from the search process considered.

In the Medicare health plan market, the assumption of exhaustive search is more appropriate as often data that are available for one plan are available for many other plans at the same time. For instance, the Medicare website compares several plans across whatever characteristics are chosen, similar to other websites such as plan prescriber (www.planprescriber.com). The more likely decision may therefore be whether to search at all instead of whether to search *one more time*. To some extent, this search process is also data driven. We cannot allow for a fully sequential search model because we can never be sure where different beneficiaries have searched. Even if we knew how many plans someone looked at, there would be generally too many combinations of different plans to identify utility and search cost coefficients. As discussed in Section 4, we split beneficiaries into informed and uninformed groups based on how many avenues they took to gain information, taking one or less implies they are uninformed while taking two or more implies they are informed.

5.1 Utility Specification

We allow for two separate utility specifications, one for informed and one for uninformed beneficiaries. In both cases, we adopt the standard random coefficient multinomial probit (RCMNP) model.[14] For informed buyers, the latent utility for beneficiary i is determined by

$$u_{ij} = \mathbf{x}_j \beta_i + \epsilon_{ij}, \tag{1}$$

[14] One important justification of the RCMNP model is to avoid Independence of Irrelevant Alternatives (IIA). See Athey and Imbens (2007) for more detail.

where $\mathbf{x}_j = (x_{1j}, ..., x_{K_1 j})'$ is the $K_1 \times 1$ vector of plan characteristics, K_1 is the number of plan characteristics relevant for informed beneficiaries, and $\epsilon_{ij} \overset{iid}{\sim} N(0,1)$, independent of $\mathbf{X}$. For uninformed eligibles, denote by $\tilde{\mathbf{x}}_j$ the subset of $\mathbf{x}_j$ consisting of K_2 characteristics on which all beneficiaries are informed, with corresponding coefficients $\tilde{\beta}_i$. Therefore, the latent utility for (uninformed) beneficiary i is determined by

$$\tilde{u}_{ij} = \tilde{\mathbf{x}}_j \tilde{\beta}_i + \tilde{\epsilon}_{ij}. \tag{2}$$

Again, $\tilde{\epsilon}$ and $\tilde{\mathbf{x}}_j$ are independent for all j and $\tilde{\epsilon}_{ij} \overset{iid}{\sim} N(0,1)$. We also assume that $\tilde{\epsilon}$ and ϵ are independent.

We specify the random coefficients for informed buyers as follows:

$$\beta_i' = \mathbf{z}_i' \Delta + \nu_i, \text{ where } \nu_i \overset{iid}{\sim} N\left(0, V_\beta\right), \tag{3}$$

where $\mathbf{z}_i$ is the $D \times 1$ vector of demographic variables, Δ is a $D \times K_1$ matrix of common coefficients, and V_β is a $K_1 \times K_1$ covariance matrix. The analogous equation for uninformed beneficiaries is

$$\tilde{\beta}_i' = \mathbf{z}_i' \tilde{\Delta} + \tilde{\nu}_i, \text{ where } \tilde{\nu}_i \overset{iid}{\sim} N\left(0, V_{\tilde{\beta}}\right), \tag{4}$$

where $\tilde{\Delta}$ is now a $D \times K_2$ matrix of common coefficients, and $V_{\tilde{\beta}}$ is a $K_2 \times K_2$ variance matrix.

Note that this approach allows for demographic and plan characteristic interactions as well as unobserved heterogeneity in preferences. We use demeaned values for demographic explanatory variables. This simplifies interpretation so that the constant terms represent marginal utilities for the average beneficiary. For instance, if x_1 is premium, then Δ_1 represents the marginal effect of premium for a beneficiary of average age, average income, average education and so forth.

5.2 Search Rule

Since buyers know their maximum utilities prior to search, but not which plan offers which utility, the benefit from search is

$$b_i = \max\{u_{i1}, ..., u_{iJ}\} - \max\{\tilde{u}_{i1}, ..., \tilde{u}_{iJ}\}. \tag{5}$$

This is just the difference between the potential utility available through costly search and the guaranteed utility everyone can obtain without searching. Since each beneficiary potentially observes different utility values, each b_i also differs across eligibles.

This benefit of search is also the minimum (for uninformed buyers) or maximum (for informed buyers) search cost. Denote these minima and maxima for each i beneficiary by $\underline{m}_i$ and $\bar{m}_i$, respectively. The main focus of this paper is to explain the primary determinants of these critical search cost values. To do so, we specify the following functional forms:

$$\begin{aligned} \bar{m}_i &= \mathbf{w}_i \gamma + \mu_i, \\ \underline{m}_i &= \mathbf{w}_i \tilde{\gamma} + \tilde{\mu}_i, \end{aligned} \tag{6}$$

where $\mathbf{w}_i$ is a $1 \times M$ vector of demographics for both informed and uninformed beneficiaries. We assume the error terms, μ_i for informed and $\tilde{\mu}_i$ for uninformed, are iid with $\mu_i \sim N(0, \sigma^2)$ and $\tilde{\mu}_i \sim N(0, \tilde{\sigma}^2)$.

We identify search cost coefficients through two avenues. One, the level of information is observed in the data, as discussed in Section 4, so that beneficiaries are matched to one of two information types. Two, we include in $\mathbf{w}_i$ certain demographics that are excluded from $\mathbf{z}_i$, such as the number of helpers assisting the beneficiary and race, so that there is an exogenous source of variation within beneficiaries of a particular information structure. This provides the necessary independent variation between search and taste heterogeneities, as mentioned in Section 3. Our specification therefore introduces a second type of heterogeneity into the standard discrete choice model, allowing for both heterogeneity in taste, due to the random coefficients, as well as heterogeneity in information.

More generally, we assume a single search cost distribution from which all beneficiaries have some unobserved search cost. We make no restrictions on this distribution and instead restrict the minimum and maximum search costs (i.e., search cost cutoffs) to follow normal distributions. From these minima and maxima, and from our assumed search process discussed previously, we know on which side of these cutoffs each beneficiary lies. We can then determine, among uninformed beneficiaries, who is most likely to benefit from small information improvements. This tells us who needs the smallest push in order to become informed.

Figure 1 provides a graphical exposition. The distribution itself represents the full, unconditional search cost distribution, while the lines, $\underline{m}_a$ and $\underline{m}_b$, represent the mean estimated cutoff values for two uninformed beneficiaries (i.e., the minimum search costs). The true search costs, s_a and s_b, lie somewhere to the right of the respective minima. To better understand our results, assume that a given demographic component, w_1, has the following relationship across the two beneficiaries: $w_{1a} < w_{1b}$. For instance, beneficiary b's income level exceeds that of beneficiary a. Further assume that $\tilde{\gamma}_1 > 0$, which in this case implies that income has a positive effect on uninformed beneficiaries' minimum search costs. Therefore, beneficiary b has a higher minimum search cost than beneficiary a, as depicted in the graph. It follows that beneficiary b is more likely to have a search cost closer to their cutoff than beneficiary a, and we interpret this to mean that beneficiary b is more likely to make an informed decision in response to a uniform decrease in all beneficiary search costs. We can also think of this in terms of the benefit to search, in which case beneficiary a has a smaller benefit to search than beneficiary b. This again implies that, if we could lower the search costs of both people, beneficiary b would be more likely to search than beneficiary a. Since a given beneficiary would only search if the utility gain exceeds their search cost, "becoming informed" is completely welfare improving (or at least not welfare decreasing).

FIGURE 1 GOES HERE

5.3 Decision Rule

To study the final decision rule, we denote by y_i the plan chosen by beneficiary i. For $y_i = j$, we therefore know the following:

1. If uninformed, then the beneficiary's utility is $\tilde{u}_{ij} = \max\{\tilde{u}_{ij}, ..., \tilde{u}_{ij}\}$ and

$$\underline{m}_i = \max\{u_{i1}, ..., u_{iJ}\} - \tilde{u}_{ij},$$

   and

2. If informed, then the beneficiary's utility is $u_{ij} = \max\{u_{i1}, ..., u_{iJ}\}$ and

$$\bar{m}_i = u_{ij} - \max\{\tilde{u}_{ij}, ..., \tilde{u}_{ij}\}.$$

To back out critical search costs, note that for uninformed buyers, all u_{ij} are formed by taking the counterfactual—*if* beneficiary i were informed, then their utilities would be $u_{ij}, ..., u_{iJ}$—and similarly for informed buyers.

6 Estimation

To estimate utility and search cost coefficients, we use a Bayesian Markov Chain Monte Carlo (MCMC) approach. We specify prior distributions for Δ, $\tilde{\Delta}$, V_β, $V_{\tilde{\beta}}$, γ, $\tilde{\gamma}$, σ^2 and $\tilde{\sigma}^2$ in order to obtain draws from the posterior distributions. We follow Athey and Imbens (2007) as well as Rossi, McCulloch and Allenby (1996) and Chib and Greenberg (1998) in our sampling algorithm. The basic idea is as follows:[15]

1. Draw latent utilities for informed and uninformed beneficiaries, $\{\mathbf{u}_1, ..., \mathbf{u}_{N_1}\}$ and $\{\tilde{\mathbf{u}}_1, ..., \tilde{\mathbf{u}}_{N_2}\}$ respectively. Recall from Section 5.1, informed and uninformed utilities take the form of $u_{ij} = \mathbf{x}_j \beta_i + \epsilon_{ij}$ and $\tilde{u}_{ij} = \tilde{\mathbf{x}}_j \tilde{\beta}_i + \tilde{\epsilon}_{ij}$, respectively. Conditional on each set of parameters, utilities therefore follow a normal distribution with mean and variance provided in Appendix A. We obtain draws of each plan's utility for each beneficiary as follows: (1) draw the utility of the chosen option from a conditional normal distribution, truncated below by 0; and (2) draw the remaining utilities from a conditional normal distribution, truncated above by the utility of the chosen option.[16]

2. Draw corresponding random utility coefficients, β_i for $i = 1, ..., N_1$ and $\tilde{\beta}_i$ for $i = 1, ..., N_2$. Recall from Section 5.1, random coefficients for informed and uninformed beneficiaries take the form of $\beta_i' = \mathbf{z}_i' \Delta + \nu_i$ and $\tilde{\beta}_i' = \mathbf{z}_i' \tilde{\Delta} + \tilde{\nu}_i$, respectively. Conditional on utilities from the previous step, random coefficients again follow a normal distribution with mean and variance provided in Appendix A.

3. Draw common coefficients Δ and $\tilde{\Delta}$. This stage is essentially a regression of random parameters on demographic variables. As such, conditional on the random parameters from the previous step, common coefficients follow a normal distribution with mean and variance given in Appendix A.

[15]For a more formal discussion of our estimation procedure, see Appendix A.

[16]We draw the utility for the chosen option using the inverse transform method and draw the remaining utilities using the accept/reject method.

4. Draw variance matrices V_β and $V_{\tilde{\beta}}$. Conditional on the parameters from the preceding steps, each variance matrix follows an inverted Wishart distribution with inverse scale matrix and degrees of freedom provided in Appendix A.

5. Form benefits $\{b_1, ..., b_N\}$ as well as maximum search costs, $\{\bar{m}_1, ..., \bar{m}_{N_1}\}$ and minimum search costs, $\{\underline{m}_1, ..., \underline{m}_{N_2}\}$. To form these values, we pose a counterfactual. For example, consider an uninformed beneficiary with demographic variables $\mathbf{z}_1$. From the first 3 steps, we have an estimate of $\max\{\tilde{u}_{11}, ..., \tilde{u}_{1J}\}$ and a draw of Δ. From $\mathbf{z}_1$ and Δ, we obtain a draw of β with mean $\mathbf{z}_1^{'}\Delta$. We then obtain draws of $\{u_{11}, ..., u_{1J}\}$, find the maximum of such draws and take the difference from this maximum and $\max\{\tilde{u}_{11}, ..., \tilde{u}_{1J}\}$. This difference provides a draw of $\underline{m}_1$.

6. Draw search cost coefficients γ and $\tilde{\gamma}$. Given the minimum and maximum search costs, this step is essentially a regression of maximum and minimum search costs on demographic variables. Conditional on search costs, γ and $\tilde{\gamma}$ therefore follow a normal distribution with mean and variance given in Appendix A.

7. Draw search cost variances σ^2 and $\tilde{\sigma}^2$. Analogous to V_β and $V_{\tilde{\beta}}$, search cost variances follow an inverted gamma distribution conditional on previous parameter draws with shape and scale provided in Appendix A.

In each step, we draw from distributions conditional on the previous coefficient draws. We adopt the standard discrete choice framework and study utilities in relation to a base option available to all beneficiaries. Since all beneficiaries have the option of FFS, we use basic Medicare FFS as the default plan. This means that our plan characteristic variables, $\mathbf{x}_j$ and $\tilde{\mathbf{x}}_j$, are actually differenced by the level of each characteristic offered under the standard Medicare FFS. Similarly, ϵ_{ij} and $\tilde{\epsilon}_{ij}$ represent differenced error terms. This normalizes the basic Medicare FFS plan to zero utility and implies that all other latent utilities are relative to this base level.

We follow the steps above for 50,000 draws. For Δ, $\tilde{\Delta}$, V_β and $V_{\tilde{\beta}}$, we drop the first 10,000 draws and take each 20th draw to form the posterior distributions. In this case, the Geweke Separated Partial Means (GSPM)[17] test yields p-values above 0.5 for most coefficients and above 0.1 for all coefficients, suggesting our simulators successfully converged to their

[17]The GSPM test determines whether the mean from the first 10% of the MCMC draws is identical to the mean of the final 50% of the draws. See Geweke (2005) for more detail. We also ran the model with 75,000 draws with no noticeable change in the results.

respective posterior distributions. Since draws of search cost coefficients depend strongly on utility coefficients and variances, we drop an additional 10,000 draws for these coefficients. This amounts to dropping the first 20,000 draws for γ, $\tilde{\gamma}$, σ^2 and $\tilde{\sigma}^2$. Similar convergence diagnostics yield p-values above 0.3 for both informed and uninformed search cost coefficients.

7 Results

For all sets of coefficients, we follow Rossi, McCulloch, and Allenby (1996) and indicate the probability of coefficients being the same sign as the posterior mean with a * for at least 80% probability and ** with at least 90% probability. This gives us some feel for which coefficients are sufficiently far from zero.

7.1 Utility Coefficients

Results for informed beneficiaries are in Table 5, and results for uninformed beneficiaries are in Table 6.[18] These tables present the posterior means for Δ and $\tilde{\Delta}$, respectively, with posterior standard deviations in parentheses. As mentioned in Section 5.1, all demographic variables are demeaned so that the constant term represents the average effect across all beneficiaries. Also note that Inpatient Hospital Care (IHC), Skilled Nursing Facility (SNF) care and premium are measured in \$100s while doctor and specialist co-pay is measured in \$10s. Therefore, for informed beneficiaries, the constant for premium implies that the average informed beneficiary's expected utility decreases by 0.193 as the plan's premium increases by \$100, all else constant. Similarly, expected utility for an average informed beneficiary decreases by 0.180 in response to a \$100 per day increase to stay in a Skilled Nursing Facility.

Tables 5 and 6 go here

The remaining coefficients represent interaction terms between beneficiary demographics and plan characteristics. For instance, consider the coefficient for the plan characteristic titled "Extra" and the demographic variable "# Chronic Diseases". The posterior mean of 0.042 implies that beneficiaries with more chronic diseases place more value on health education and acupuncture services than beneficiaries with fewer chronic diseases. Similarly, beneficiaries with

[18] For brevity, estimated covariance matrices for informed and uninformed beneficiaries are relegated to the Appendix.

better self-reported health status care more about such services than those reporting poor health (recall larger values of this variable indicate poorer health).

From Table 6 we see that posterior means are generally further away from zero than for informed beneficiaries with smaller relative variances. The constant term still represents the average effect across uninformed beneficiaries. The most important difference is premium, on which uninformed beneficiaries put far more weight than informed beneficiaries. This makes sense as premium is one of the more easily observed plan characteristics. Therefore, uninformed beneficiaries are much more attracted to lower premium plans. Specifically, a \$100 increase in premium or a \$10 increase in co-pay decreases the expected utility of an average uninformed beneficiary by 3.541 and 0.352, respectively. For the interaction terms, we see that uninformed beneficiaries in good health tend to value prescription drug coverage more than beneficiaries reporting poor health. Also note the large negative effect of co-pay for beneficiaries with diabetes. This implies that uninformed beneficiaries with diabetes are more negatively affected by a high doctor and specialist co-pay than those without diabetes, which is intuitively clear as these beneficiaries are more likely to need such visits. As we discuss further in the next Section, this effect for diabetes has important implications for search behavior.

7.2 Information Structure

We can now discuss search behavior and determinants of critical search costs, the main focus of the paper. Posterior means of minimum search cost coefficients for uninformed beneficiaries are included in Table 7. These minimum search costs represent the smallest possible search cost a beneficiary could have had in order to still have made an uninformed decision. The coefficients themselves represent marginal effects on these minima. Recall from our discussion of Figure 1 that, for uninformed beneficiaries, a larger minimum search cost implies that this beneficiary is more likely to have a search cost close to their minimum and vice versa for smaller minimum search costs. Specifically, the positive coefficient for age means that being one year older increases the expected minimum search cost by 0.005. Similarly, moving up one income bracket increases the expected minimum search cost by 0.010. Self-reported health status and race also have positive effects. Together, these results imply that older, higher income, African American beneficiaries with poor self-reported health status are more likely to utilize easier access to information.

Table 7 goes here

Conversely, employed beneficiaries with diabetes and extra assistance are less likely to utilize improved access to information. For employed beneficiaries, this is intuitively clear as they may have some non-medicare coverage through their employer. This also makes sense for those with extra household assistance and diabetes as these beneficiaries are more likely to have someone making their decision for them and therefore much less likely to search. Recall that this analysis is conditional on being uninformed. Therefore, this does not imply that someone with diabetes benefits less from search—only someone with diabetes who was observed to make an uninformed decision.

Although our policy discussion pertains mainly to uninformed beneficiaries, we include results for informed beneficiaries in Table 8. In this case, coefficients represent marginal effects for maximum search costs—the largest possible search cost a person could have had in order to still make an informed decision. Our interpretation in this case is slightly different. Here, a lower maximum search cost implies that these beneficiaries must have relatively low search costs in order to have made an informed decision. This also implies that such beneficiaries were closer to making an uninformed decision. Therefore, since the posterior mean for diabetes is negative and sufficiently far from zero, informed beneficiaries with diabetes are more likely closer to making an uninformed decision than those without diabetes. A similar interpretation holds for informed beneficiaries with more chronic diseases. This is somewhat surprising as we might initially expect diabetics to have a very large benefit to search. Intuitively, however, this result derives primarily from taste differences among diabetics, where we see from Table 6 that uninformed beneficiaries with diabetes place substantial weight on co-pay and prescription drug coverage. Therefore, utility differences between informed and uninformed are smaller for those with diabetes as opposed to, for instance, someone with a strong education. In this case, our assumption that uninformed beneficiaries still observe co-pay is important. If we eliminated co-pay from the uninformed beneficiaries' information sets, the benefit to search for diabetics would be substantially higher.

Table 8 goes here

As mentioned previously, the policy implication for our model is that older, higher income, African American beneficiaries with lower self-reported health status need less help to go from uninformed to informed. Note that this interpretation holds for uninformed beneficiaries and is therefore conditional on the information structure. This does not mean that such a beneficiary is more or less likely to be informed. It means that, conditional on being uninformed, these types of beneficiaries need less of a push in order to make an informed decision. This has important policy implications if we imagine wanting to target beneficiaries most likely to use new information. This result could not be attained, for instance, with a standard reduced-form probit model using informed or uninformed as the dependent variable.[19] Such a model would only determine which types of beneficiaries are more likely to be informed or uninformed—not who is *closer* to being informed conditional on being uninformed.

8 Conclusion

This paper introduces consumer search into a discrete choice model while accounting for horizontal taste differentiation across plans. A major underlying premise is that information structures are due both to general demographic characteristics as well as taste differences. We estimate a RCMNP model where beneficiaries are either informed or uninformed and have different decision processes accordingly. Using these utility coefficients, we model a consumer search process and estimate critical search cost coefficients.

Our analysis provides two main contributions, one of which is more econometric and the last more policy oriented. One, due to strong differences across coefficients, there is evidence that information heterogeneities are an important determinant of plan choice. Ignoring such heterogeneities may have important implications. Two, we address these informational heterogeneities with a consumer search model while still accounting for horizontal taste differentiation. This assumes that all beneficiaries are capable of understanding the health plans available to them, but it may be overly costly for some of them to do so. This allows us to study how close beneficiaries must have been to making an informed or uninformed decision. For example, our search cost coefficients imply that higher income beneficiaries are most likely closer to their threshold search cost values than lower income beneficiaries, while beneficiaries with more assistance are more likely to have search costs well away from the cutoff. This implies that high income, older beneficiaries with little household assistance will benefit more from easier access to information than younger, low income beneficiaries with more assistance.

[19] For completeness, results for such a model, as well as for a standard count model using the level of information as the dependent variable, are included in Table 9 in the Appendix.

A Gibbs Sampler Algorithm

Denote by $\underline{N}(t, \mu, \sigma^2)$ a normal distribution truncated below by t and by $\overline{N}(t, \mu, \sigma^2)$ a normal distribution truncated above by t. We consider the following conjugate (and diffuse) priors:

$$\begin{aligned} \Delta &\sim N(0, V_\Delta) & \tilde{\Delta} &\sim N(0, V_{\tilde{\Delta}}) \\ V_\beta^{-1} &\sim W(\mu_{V_\beta}, I_{K_1}) & V_{\tilde{\beta}}^{-1} &\sim W(\tilde{\mu}_{V_{\tilde{\beta}}}, I_{K_2}) \\ \gamma &\sim N(\mu_\gamma, V_\gamma) & \tilde{\gamma} &\sim N(\mu_{\tilde{\gamma}}, V_{\tilde{\gamma}}) \\ \sigma^2 &\sim IG(a, b) & \tilde{\sigma}^2 &\sim IG(\tilde{a}, \tilde{b}) \end{aligned}$$

Given these priors, we sample from the conditional distributions as follows:

1. Draw latent utilities:

$$\begin{aligned} \tilde{u}_{ij} | \tilde{\mathbf{x}}_j, (y_i = j), (\phi = 0), \tilde{\beta}_i &\sim \underline{N}\left(\max_{l \neq j}\{\tilde{u}_{il}\}, \tilde{\mathbf{x}}_j \tilde{\beta}_i, 1\right) \forall (i, j) \\ \tilde{u}_{ik} | \tilde{\mathbf{x}}_k, (y_i = j), (\phi = 0), \tilde{\beta}_i &\sim \overline{N}\left(\tilde{u}_{ij}, \tilde{\mathbf{x}}_k \tilde{\beta}_i, 1\right) \forall (i, k \neq j) \\ u_{ij} | \mathbf{x}_j, (y_i = j), (\phi = 1), \beta_i &\sim \underline{N}\left(\max_{l \neq j}\{u_{il}\}, x_j \beta_i, 1\right) \forall (i, j) \\ u_{ik} | x_k, (y_i = j), (\phi = 1), \beta_i &\sim \overline{N}\left(u_{ij}, x_k \beta_i, 1\right) \forall (i, k \neq j) \end{aligned}$$

2. Draw random utility coefficients:

$$\begin{aligned} \tilde{\beta}_i | \tilde{\mathbf{u}}_i, \tilde{\mathbf{X}} &\sim N\left((\tilde{\mathbf{X}}'\tilde{\mathbf{X}} + V_{\tilde{\beta}}^{-1})^{-1}(\tilde{\mathbf{X}}'\tilde{\mathbf{u}}_i + \mathbf{z}_i \tilde{\Delta} V_{\tilde{\beta}}^{-1}), (\tilde{\mathbf{X}}'\tilde{\mathbf{X}} + V_{\tilde{\beta}}^{-1})^{-1}\right) \\ \beta_i | \mathbf{u}_i, \mathbf{X} &\sim N\left((\mathbf{X}'\mathbf{X} + V_\beta^{-1})^{-1}(\mathbf{X}'\mathbf{u}_i + \mathbf{z}_i \Delta V_\beta^{-1}), (\mathbf{X}'\mathbf{X} + V_\beta^{-1})^{-1}\right) \end{aligned}$$

3. Draw common coefficients:

$$\begin{aligned} &\tilde{\Delta} | \bar{\beta} = \left(\tilde{\beta}_1, ..., \tilde{\beta}_{N_2}\right)', \mathbf{Z} = \left((I_{K_2} \otimes \mathbf{z}_1'), ..., (I_{K_2} \otimes \mathbf{z}_{N_2}')\right)' \\ &\quad \sim N\left((\mathbf{Z}'(I_{N_2} \otimes V_{\tilde{\beta}}^{-1})\mathbf{Z} + (I_{K_2} \otimes V_{\tilde{\Delta}}^{-1})^{-1}(\mathbf{Z}'(I_{N_2} \otimes V_{\tilde{\beta}}^{-1})\bar{\beta}), (\mathbf{Z}'(I_{N_2} \otimes V_{\tilde{\beta}}^{-1})\mathbf{Z} + (I_{K_2} \otimes V_{\tilde{\Delta}}^{-1})^{-1}\right) \\ &\Delta | \bar{\beta} = \left(\beta_1, ..., \beta_{N_1}\right)', \mathbf{Z} = \left((I_{K_1} \otimes \mathbf{z}_1'), ..., (I_{K_1} \otimes \mathbf{z}_{N_1}')\right)' \\ &\quad \sim N\left((\mathbf{Z}'(I_{N_1} \otimes V_\beta^{-1})\mathbf{Z} + (I_{K_1} \otimes V_\Delta^{-1})^{-1}(\mathbf{Z}'(I_{N_1} \otimes V_\beta^{-1})\bar{\beta}), (\mathbf{Z}'(I_{N_1} \otimes V_\beta^{-1})\mathbf{Z} + (I_{K_1} \otimes V_\Delta^{-1})^{-1}\right) \end{aligned}$$

4. Draw variance matrices:

$$V_{\tilde{\beta}}^{-1}|\tilde{\beta}_i, \mathbf{z}_i, \tilde{\Delta} \sim W\left(\mu_{V_{\tilde{\beta}}} + N_2, \left(I_{K_2} + \sum_{i=1}^{N_2}\left(\tilde{\beta}_i - \mathbf{z}_i'\tilde{\Delta}\right)\left(\tilde{\beta}_i - \mathbf{z}_i'\tilde{\Delta}\right)'\right)^{-1}\right)$$
$$V_{\beta}^{-1}|\beta_i, \mathbf{z}_i, \Delta \sim W\left(\mu_{V_{\beta}} + N_1, \left(I_{K_1} + \sum_{i=1}^{N_1}\left(\beta_i - \mathbf{z}_i'\Delta\right)\left(\beta_i - \mathbf{z}_i'\Delta\right)'\right)^{-1}\right)$$

Given $\tilde{\Delta}, V_{\tilde{\beta}}^{-1}, \tilde{\mathbf{U}}, \Delta, V_{\beta}^{-1}, \mathbf{U}$, we can then estimate minimum and maximum search costs.

1. Form counter-factual utility values (i.e., if beneficiary i was informed, we estimate utility values *if* beneficiary i would have been uninformed, and vice versa):

$$\tilde{\beta}_i \sim N\left(\mathbf{z}_i\tilde{\Delta}, V_{\tilde{\beta}}\right)$$
$$\tilde{u}_{ij} \sim N\left(\tilde{\mathbf{x}}_j\tilde{\beta}_i, 1\right)$$
$$\beta_i \sim N\left(\mathbf{z}_i\Delta, V_{\beta}\right)$$
$$u_{ij} \sim N\left(\mathbf{x}_j\beta_i, 1\right)$$

2. Estimate benefit to search as well as minimum and maximum search costs:

$$b_i = \max\{u_{i1}, ..., u_{iJ}\} - \max\{\tilde{u}_{i1}, ..., \tilde{u}_{iJ}\}$$
$$\bar{m}_i|\gamma, \mathbf{w}_i \sim N\left(\mathbf{w}_i\gamma, \sigma^2\right)$$
$$b_i = \max\{u_{i1}, ..., u_{iJ}\} - \max\{\tilde{u}_{i1}, ..., \tilde{u}_{iJ}\}$$
$$\underline{m}_i|\tilde{\gamma}, \mathbf{w}_i \sim N\left(\mathbf{w}_i\tilde{\gamma}, \tilde{\sigma}^2\right).$$

3. Draw search cost coefficients:

$$\gamma|\mathbf{W}, \sim N\left((\mathbf{W}'\mathbf{W}/\sigma^2 + V_{\gamma}^{-1})^{-1}(\mathbf{W}'\bar{\mathbf{m}}/\sigma^2 + V_{\gamma}^{-1}\mu_{\gamma}), (\mathbf{W}'\mathbf{W}/\sigma^2 + V_{\gamma}^{-1})^{-1}\right)$$
$$\tilde{\gamma}|\mathbf{W}, \sim N\left((\mathbf{W}'\mathbf{W}/\tilde{\sigma}^2 + V_{\tilde{\gamma}}^{-1})^{-1}(\mathbf{W}'\underline{\mathbf{m}}/\tilde{\sigma}^2 + V_{\tilde{\gamma}}^{-1}\mu_{\tilde{\gamma}}), (\mathbf{W}'\mathbf{W}/\tilde{\sigma}^2 + V_{\tilde{\gamma}}^{-1})^{-1}\right)$$

4. Draw search cost variances:

$$\sigma^2|\bar{\mathbf{m}}, \mathbf{W}, \gamma \sim IG\left(N_1/2 + a, \left[b^{-1} + (1/2)(\bar{\mathbf{m}} - \mathbf{W}\gamma)'(\bar{\mathbf{m}} - \mathbf{W}\gamma)\right]^{-1}\right)$$
$$\tilde{\sigma}^2|\underline{\mathbf{m}}, \mathbf{W}, \tilde{\gamma} \sim IG\left(N_2/2 + \tilde{a}, \left[\tilde{b}^{-1} + (1/2)(\underline{\mathbf{m}} - \mathbf{W}\tilde{\gamma})'(\underline{\mathbf{m}} - \mathbf{W}\tilde{\gamma})\right]^{-1}\right).$$

B Simulation Results

To test our estimation procedure, we simulate a simple model with $N = 2000$ (1000 informed and 1000 uninformed) beneficiaries choosing among $J = 5$ plans, where beneficiaries have random coefficients discussed in the model description. The data generating process is as follows.

- Plan characteristics for informed buyers
  - Disease 1 Coverage: Binomial with $P(X=0) = 0.2$, $P(X=1) = 0.6$ and $P(X=2) = 0.2$
  - Disease 2 Coverage: Bernoulli with $P(X=0) = 0.5)$
  - (-) Premium: $-\exp N(0,1)$
- Plan characteristics for uninformed buyers
  - Disease 2 Coverage: Bernoulli with $P(X=0) = 0.5)$
  - (-) Premium: $-\exp N(0,1)$
- Demographics for both informed and uninformed
  - Log of income: $\ln(40000) + \frac{\ln(3000)}{1.96} N(0,1)$
  - Disease 1 indicator: Bernoulli with $P(X=0) = 0.6$
  - Disease 2 indicator: Bernoulli with $P(X=0) = 0.5$
- Outside good for both informed and uninformed
  - Disease 1 Coverage: 1
  - Disease 2 Coverage: 0
  - Premium: \$0

Our simulated data assume that the variance matrices of random coefficients for informed and uninformed beneficiaries are $.1 \times I_3$ and $.1 \times I_2$, respectively, and the common utility coefficients are

	Plan Characteristics		
Demographics	Disease 1 Coverage	Disease 2 Coverage	(-) Premium
Constant	1	-1	2
Log of Income (demeaned)	0	0	-0.1
Disease 1 (demeaned)	0.5	0	0
Disease 2 (demeaned)	0	0.5	0

for informed beneficiaries and

	Plan Characteristics	
Demographics	Disease 2 Coverage	(-) Premium
Constant	1	2
Log of Income (demeaned)	0	0.2
Disease 1 (demeaned)	0.2	0
Disease 2 (demeaned)	0	-0.2

for uninformed beneficiaries.

C Reduced Form Information Structure

As an initial assessment of beneficiary information structure, we consider a standard Poisson count model with the level of information as the dependent variable and age, health status, income, education and other demographics as the independent variables. Results are included in Table 9. A common problem with the Poisson model, however, is that it underfits dispersion in the dependent variable. To account for this, we run a Negative Binomial model, also included in Table 9. Although coefficients essentially do not change, a likelihood-ratio test for $\alpha = 0$ concludes that there is significant evidence of overdispersion, suggesting a preference for the Negative Binomial model.

Table 9 goes here

The interpretations essentially do not change across the two models. We see that age is positively related to gaining information, age (in tens of years) squared is negatively related, and that education and the number of chronic diseases are positively related. More specifically, we see from the factor changes that becoming one year older increases the expected number of information resources used by a factor of about 1.2. Similarly, increasing education by one level (e.g., going from some college to gaining a college degree) or having one more chronic disease increases the expected number of information resources used by a factor of 1.07 and 1.11, respectively.

As a robustness check, we also form an indicator variable for whether the beneficiary is informed or not, as per our definition of informed in Section 4. We do this because our consumer search process similarly splits buyers into two groups, and we want to ensure that imposing this type of cutoff does not drive our results. From the probit model, also included in Table 9, we see that for sign and significance, most coefficients do not change. We conclude that any major differences between our search cost coefficients and the probit or count model coefficients are probably not attributed to our assignment of beneficiaries into one of only two groups.

D Variance-covariance Matrices for Utility Coefficients

Tables 10 and 11 go here

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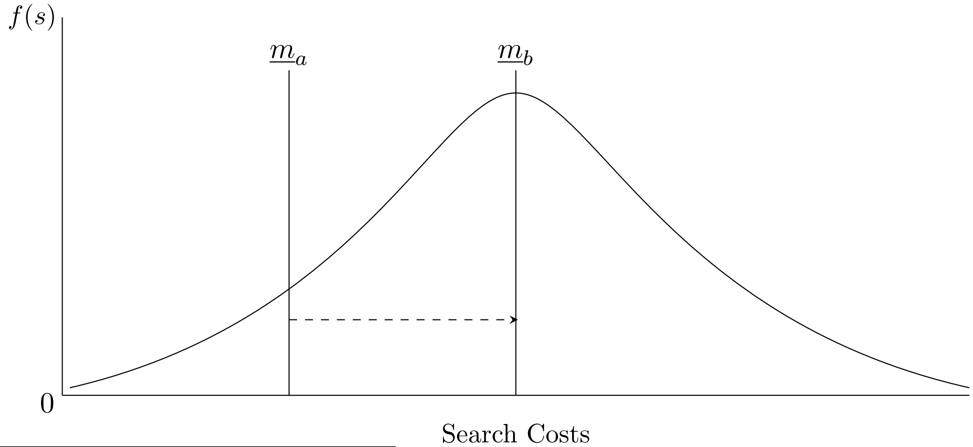
Figure 1: PREDICTED MINIMUM SEARCH COSTS FOR UNINFORMED BENEFICIARIES[a]



[a]This depicts the movement of a predicted minimum search cost from m_a to m_b and represents the effect of variables with positive search cost coefficients on the minimum search cost of a given beneficiary. The interpretation is that beneficiary b is more likely closer to their minimum search cost than beneficiary a, and therefore, beneficiary b needs less “push” (probabilistically) to make an informed decision.

Table 1: Definitions and Summary Statistics for Plan Characteristic Variables

Variable Name	Definition	Measurement	Mean	Std	Min	Max
Premium	Monthly premium (in addition to Part B premium)	Dollars	$45.86	$43.76	$0	$304
Inpatient Hospital Care	Average out-of-pocket cost for 90 day stay in hospital	Dollars	$19.71	$60.81	$0	$295
Skilled Nursing Facility	Average out-of-pocket cost for 20 day stay in skilled nursing facility	Dollars	$9.27	$28.44	$0	$175
Co-pay	Average doctor or specialist co-payment	Dollars	$12.94	$6.83	$0	$80

Variable Name	Definition	Measurement	Percentage	Mean
Hearing Services	Hearing services covered (in addition to basic Medicare coverage)	0 for no extra coverage	35.84	1.11
		1 for some coverage	26.77	
		2 for one free service	28.10	
		3 for tests and hearing aids free	9.29	
Extra	Health education and acupuncture coverage	0 for neither	21.90	0.80
		1 for education/acupuncture	75.88	
		2 for both	2.21	
Home Health	Coverage for home health care visits	0 for no coverage	0.22	1.94
		1 for some co-payment	5.53	
		2 for free home health visits	94.25	
Prescription Drug Coverage	Total drug coverage	0 for no coverage	33.85	1.09
		1 for generic coverage	23.67	
		2 for generic and brand name coverage	42.48	
Dental	Dental services covered	0 for no coverage	74.56	0.65
		1 for some coverage	8.63	
		2 for one service free	5.31	
		3 for two services free	3.98	
		4 for three services free	4.20	
		5 for four services free	3.32	
Vision	Vision services covered (in addition to basic Medicare coverage)	0 for no coverage	17.04	1.42
		1 for some coverage	40.49	
		2 for up to two services free	25.66	
		3 for more than two services free	16.81	
Physical Exam	Routine physical exam coverage	0 for no coverage	2.88	1.36
		1 for some co-payment	57.96	
		2 for no co-payment	39.16	
			$N = 452$	

Table 2: Definitions and Summary Statistics for Demographic Variables

Variable Name	Measurement	Mean	Std
Age	Years of age	76.30	7.30
GHPs available	Total number of group health plans available in beneficiary's area	4.23	3.16
Risk plans available	Total number of risk plans available in beneficiary's area	3.40	2.93
Number of helpers	Total number of people reported to have helped beneficiary in some way	0.63	0.77

Variable Name	Measurement	Percentage	Mean
Income	1 for $5,000 or less	3.58	4.87
	2 for $5,001 to $10,000	13.03	
	3 for $10,001 to $15,000	23.32	
	4 for $15,001 to $20,000	16.11	
	5 for $20,001 to $25,000	11.91	
	6 for $25,001 to $30,000	8.95	
	7 for $30,001 to $35,000	5.15	
	8 for $35,001 to $40,000	5.15	
	9 for $40,001 to $45,000	2.78	
	10 for $45,001 to $50,000	2.82	
	11 for $50,001 or more	7.21	
Education	1 for no school	1.70	4.41
	2 for no more than 8th grade	15.44	
	3 for some high school without diploma	17.82	
	4 for high school diploma	29.14	
	5 for technical or vocational school	6.27	
	6 for some college without degree	15.53	
	7 for associate's degree	3.04	
	8 for bachelor's degree	6.54	
	9 for post-graduate degree	4.52	
General health status	1 for excellent	18.17	2.63
	2 for very good	28.16	
	3 for good	31.78	
	4 for fair	15.98	
	5 for poor	5.91	
Number of Chronic Diseases	0	51.12	0.67
	1	33.93	
	2	11.91	
	3	2.60	
	4	0.45	
Diabetes	0 for no problems	81.42	0.19
	1 for some problems	18.58	
Employed	0 for no	88.36	0.12
	1 for yes	11.64	
Smoke	0 for never	36.97	0.63
	1 for sometimes	63.03	
Gender	0 for female	53.13	0.47
	1 for male	46.87	
White	0 for no	17.41	0.83
	1 for yes	82.59	
Black	0 for no	88.94	0.11
	1 for yes	11.06	
Other Race	0 if white or black	93.64	0.06
	1 if neither white or black	6.36	
		$N = 2,234$	

Table 3: DEFINITIONS AND MEANS OF SELF-REPORTED BENEFICIARY INFORMATION VARIABLES

Variable Name	Measurement	Mean
Switch plans this year	0 if no 1 if yes	0.02
Very easy to understand Medicare	0 if no 1 if yes	0.19
Easy to understand Medicare	0 if no 1 if yes	0.42
Hard to understand Medicare	0 if no 1 if yes	0.21
Very hard to understand Medicare	0 if no 1 if yes	0.07
Informed of payment info	0 if no 1 if yes	0.06
Informed of benefit info	0 if no 1 if yes	0.05
Informed of Medicare coverage info	0 if no 1 if yes	0.07
Informed of HMO info	0 if no 1 if yes	0.04
Read "Medicare and You" book	0 if no 1 if yes	0.43
Looked at quality ratings	0 if no 1 if yes	0.07
Looked at plan info chart	0 if no 1 if yes	0.13
Called Medicare hotline	0 if no 1 if yes	0.13
Visited Medicare website[a]	0 if no 1 if yes	0.03

[a]Only pertains to those who own a computer with internet access

Table 4: TABULATION OF BENEFICIARIES' INFORMATION LEVELS

Level of Information[a]	Frequency	Percentage
0	1,007	45.08
1	600	26.86
2	300	13.43
3	185	8.28
4	92	4.12
5	28	1.25
6	15	0.67
7	6	0.27
8	1	0.04
	$N = 2,234$	

[a]Determined by the sum of 11 indicators: (1) whether the beneficiary switched plans within the past year, (2-4) whether they are informed of Medicare payment, benefit or coverage information, (5) whether they are informed of HMO information, (6) whether they read the "Medicare and You" booklet, (7-8) whether they looked at quality ratings or the plan information chart, (9) whether they called the Medicare hotline, (10) whether they visited the Medicare website (provided they have internet access), and (11) whether they have someone assisting them in their Medicare decisions. Anyone with 1 or less such attempt to find information is assumed to be uninformed.

Table 5: UTILITY COEFFICIENTS FOR INFORMED BENEFICIARIES[a]

Demographic variables[c]	Posterior Means[b]										
	IHC	SNF	Premium	Co-pay	Hearing	Extra	Home Health	Pres. Drug	Dental	Vision	Phy. Exam
Constant	0.050	−0.180*	−0.193**	0.054*	0.001	0.084*	−0.137**	0.019	−0.021	−0.020	0.061
	(0.098)	(0.200)	(0.100)	(0.064)	(0.052)	(0.082)	(0.089)	(0.051)	(0.050)	(0.059)	(0.078)
Age	−0.001	−0.001	−0.002	−0.001	0.001	−0.001	0.003	−0.001	0.000	0.000	−0.001
	(0.004)	(0.009)	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Education	0.000	0.015	0.011	0.002	−0.002	−0.009	−0.007	0.002	−0.003	0.000	−0.008
	(0.021)	(0.044)	(0.023)	(0.014)	(0.012)	(0.019)	(0.021)	(0.012)	(0.011)	(0.013)	(0.018)
Income	−0.002	−0.010	0.000	−0.006	0.000	0.003	0.008	0.004	−0.002	0.005	0.000
	(0.019)	(0.037)	(0.019)	(0.014)	(0.010)	(0.016)	(0.018)	(0.010)	(0.010)	(0.012)	(0.014)
Health Status	0.014	−0.027	0.028	−0.010	−0.010	−0.033*	−0.018	0.009	−0.012	0.022	−0.012
	(0.046)	(0.088)	(0.046)	(0.029)	(0.024)	(0.038)	(0.042)	(0.023)	(0.023)	(0.026)	(0.035)
Smoke	−0.001	−0.104	−0.038	0.003	0.003	0.023	0.028	0.001	0.017	−0.015	0.032
	(0.084)	(0.160)	(0.097)	(0.061)	(0.049)	(0.077)	(0.090)	(0.048)	(0.047)	(0.057)	(0.076)
Diabetes	0.004	−0.077	−0.050	−0.020	0.004	−0.008	0.029	0.009	−0.010	0.005	−0.001
	(0.112)	(0.208)	(0.116)	(0.069)	(0.059)	(0.096)	(0.098)	(0.058)	(0.053)	(0.064)	(0.086)
Male	0.024	0.036	0.022	0.021	−0.017	−0.058	−0.050	0.022	−0.008	−0.004	−0.046
	(0.091)	(0.176)	(0.103)	(0.070)	(0.055)	(0.082)	(0.097)	(0.052)	(0.051)	(0.061)	(0.080)
# Chronic Diseases	−0.018	0.081	−0.020	0.025	−0.002	0.042*	−0.012	−0.018	0.016	−0.006	0.005
	(0.052)	(0.101)	(0.059)	(0.036)	(0.030)	(0.047)	(0.051)	(0.029)	(0.029)	(0.033)	(0.046)

[a]Informed beneficiaries are the 627 beneficiaries that tried in more than 1 way to gain information.

[b]Standard deviations are in parenthesis. A * or ** indicate at least 80% or 90% of draws are of the same sign as the posterior mean. All values represent marginal effects on utility for informed beneficiaries–for the constant, these are average marginal effects across all demographic variables.

[c]All demographic variables are demeaned in order to simplify interpretation.

Table 6: UTILITY COEFFICIENTS FOR UNINFORMED BENEFICIARIES[a]

	Posterior Means[b]		
Demographic variables[c]	Premium	Co-pay	Pres. Drug
Constant	-3.541^{**}	-0.352^{**}	0.312^{**}
	(0.370)	(0.163)	(0.171)
Age	-0.030^{**}	-0.013^{**}	0.010^{**}
	(0.012)	(0.007)	(0.007)
Education	-0.079^{*}	-0.010	0.014
	(0.079)	(0.042)	(0.044)
Income	0.149^{**}	-0.041^{**}	0.012
	(0.055)	(0.032)	(0.033)
Health Status	0.241^{**}	0.204^{**}	-0.140^{**}
	(0.123)	(0.069)	(0.074)
Smoke	-0.372^{*}	-0.022	0.104
	(0.289)	(0.159)	(0.170)
Diabetes	-0.199	-0.361^{**}	0.241^{*}
	(0.313)	(0.181)	(0.197)
Male	0.385^{**}	0.289^{**}	-0.463^{**}
	(0.291)	(0.158)	(0.180)
# Chronic Diseases	-0.301^{**}	-0.153^{**}	0.071
	(0.195)	(0.107)	(0.105)

[a]Uninformed beneficiaries are the 1,607 beneficiaries that tried in no more than 1 way to gain information.

[b]Standard deviations are in parenthesis. A * or ** indicate at least 80% or 90% of draws are of the same sign as the posterior mean. All values represent marginal effects on utility for uninformed beneficiaries–for the constant, these are average marginal effects across all demographic variables.

[c]All demographic variables are demeaned in order to simplify interpretation.

Table 7: CRITICAL SEARCH COST COEFFICIENTS FOR UNINFORMED BENEFICIARIES[a]

	Posterior Means[b]
Constant	0.001**
	(0.001)
Age	0.005**
	(0.004)
Education	0.007
	(0.012)
Income	0.010**
	(0.009)
Health Status	0.016*
	(0.021)
Smoke	0.012
	(0.048)
Diabetes	−0.040*
	(0.053)
Helpers	−0.046**
	(0.024)
Male	−0.028
	(0.046)
White	−0.021
	(0.058)
Black	0.143**
	(0.077)
Job	−0.043*
	(0.051)
# Chronic Diseases	−0.009
	(0.025)
Age^2	−0.001
	(0.004)

[a]Uninformed beneficiaries are the 1,607 beneficiaries that tried in no more than 1 way to gain information. The critical search cost represents the smallest possible search cost a person could have had in order to still make an uninformed decision. The coefficients presented represent marginal effects of these critical search costs.

[b]Standard deviations are in parenthesis. A * or ** indicate at least 80% or 90% of draws are of the same sign as the posterior mean.

Table 8: Critical Search Cost Coefficients for Informed Beneficiaries[a]

	Posterior Means[b]
Constant	-0.000
	(0.001)
Age	0.001
	(0.005)
Education	-0.003
	(0.011)
Income	0.006
	(0.008)
Health Status	0.006
	(0.019)
Smoke	0.001
	(0.044)
Diabetes	-0.061^{**}
	(0.045)
Helpers	-0.008
	(0.025)
Male	-0.025
	(0.046)
White	-0.011
	(0.095)
Black	-0.068
	(0.105)
Job	0.038
	(0.060)
# Chronic Diseases	-0.021^{*}
	(0.024)
Age^2	0.001
	(0.005)

[a]Informed beneficiaries are the 627 beneficiaries that tried in more than 1 way to gain information. The critical search cost represents the largest possible search cost a person could have had in order to still make an informed decision. The coefficients presented represent marginal effects of these maximum search costs.

[b]Standard deviations are in parenthesis. A * or ** indicate at least 80% or 90% of draws are of the same sign as the posterior mean.

Table 9: Poisson, Negative Binomial and Probit Regression Results

	Poisson[a]		Negative Binomial[a]		Probit[a,b]	
	Coefficient	Factor Change	Coefficient	Factor Change	Coefficient	Marginal Effect[c]
Age	0.170^{***}	1.185	0.141^{*}	1.151	0.122^{*}	0.048
	(0.062)		(0.075)		(0.069)	
Health Status	-0.023	0.976	-0.029	0.972	-0.055^{**}	-0.022
	(0.021)		(0.027)		(0.027)	
Male	-0.095^{**}	0.909	-0.099^{*}	0.906	-0.021	-0.008
	(0.045)		(0.058)		(0.059)	
White	0.246^{**}	1.279	0.231^{*}	1.260	0.177	0.070
	(0.097)		(0.119)		(0.112)	
Black	0.002	1.002	-0.007	0.993	0.057	0.023
	(0.117)		(0.143)		(0.134)	
Education	0.067^{***}	1.069	0.067^{***}	1.069	0.066^{***}	0.026
	(0.011)		(0.015)		(0.015)	
Income	0.005	1.005	0.008	1.009	0.014	0.005
	(0.008)		(0.011)		(0.011)	
# Chronic Diseases	0.100^{***}	1.105	0.100^{***}	1.106	0.091^{***}	0.036
	(0.025)		(0.033)		(0.035)	
Employed	-0.113^{*}	0.892	-0.107	0.899	-0.099	-0.039
	(0.066)		(0.084)		(0.089)	
Smoke	0.039	1.040	0.043	1.044	0.094	0.037
	(0.046)		(0.059)		(0.060)	
# of Helpers	-0.010	0.990	-0.010	0.990	-0.012	-0.005
	(0.031)		(0.039)		(0.040)	
Diabetes	0.023	0.977	0.025	0.975	0.021	0.008
	(0.054)		(0.069)		(0.071)	
Age^2	-0.123^{***}	0.884	$-.105^{**}$	0.901	-0.089^{**}	-0.035
	(0.040)		(0.048)		(0.044)	
Constant	1.262		1.300		-4.385	
	(0.288)		(0.369)		(2.715)	
α			0.568			
-Log Likelihood	3267.79		3145.85		1491.25	
Pseudo R^2	0.026		0.016		0.030	
N	2234		2234		2234	

[a]Results are from a count model with the number of attempted ways to find information as the dependent variable. Standard errors are in parenthesis. 90%, 95%, and 99% levels of significance are indicated by *, **, and ***, respectively.

[b]Results are from a zero/one dependent variable equal to one if beneficiary engaged in 2 or more activities to gain information and zero otherwise.

[c]Marginal effects calculated at mean values. For dummy variables, marginal effects represent changes from 0 to 1.

Table 10: COVARIANCE MATRIX FOR INFORMED UTILITY COEFFICIENTS[a]

	Posterior Means[b]										
	IHC	SNF	Premium	Co-pay	Hearing	Extra	Home Health	Pres. Drug	Dental	Vision	Phy. Exam
IHC	0.003**										
	(0.013)										
SNF	−0.007*	0.049**									
	(0.012)	(0.013)									
Premium	0.002	−0.000	0.031**								
	(0.013)	(0.012)	(0.013)								
Co-pay	−0.001	−0.001	−0.001	0.024**							
	(0.012)	(0.013)	(0.013)	(0.013)							
Hearing	0.001	−0.002	0.000	−0.001	0.018**						
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)						
Extra	−0.001	−0.000	−0.002	−0.002	−0.001	0.026**					
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)					
Home Health	−0.001	0.001	−0.004	−0.002	0.002	−0.003	0.038**				
	(0.014)	(0.012)	(0.013)	(0.013)	(0.015)	(0.013)	(0.012)				
Pres. Drug	0.002*	0.001	0.001	0.001	−0.001	−0.003*	−0.002	0.017**			
	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)			
Dental	−0.004**	0.002	0.001	−0.000	−0.002*	0.003	0.001	−0.000	0.016**		
	(0.013)	(0.0130)	(0.012)	(0.014)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)		
Vision	−0.001	0.002	0.001	0.000	−0.002*	−0.001	0.001	−0.001	−0.002	0.020**	
	(0.013)	(0.012)	(0.013)	(0.014)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	
Phy. Exam	−0.001	0.001	−0.000	-0.002	0.001	0.004*	−0.004*	−0.000	0.002*	0.001	0.025**
	(0.012)	(0.013)	(0.015)	(0.012)	(0.013)	(0.014)	(0.014)	(0.013)	(0.012)	(0.014)	(0.014)

[a]Informed beneficiaries are the 627 beneficiaries that tried in more than 1 way to gain information.
[b]Standard deviations are in parenthesis. A * or ** indicate at least 80% or 90% of draws are of the same sign as the posterior mean.

Table 11: Covariance Matrix for Uninformed Utility Coefficients[a]

	Posterior Means[b]		
	Premium	Co-pay	Pres. Drug
Premium	3.102**		
	(2.238)		
Co-pay	−0.274	2.197**	
	(1.703)	(2.925)	
Pres. Drug	−1.320**	−1.709**	2.763**
	(2.250)	(3.031)	(2.961)

[a]Uninformed beneficiaries are the 1,607 beneficiaries that tried in no more than 1 way to gain information.

[b]Standard deviations are in parenthesis. A * or ** indicate at least 80% or 90% of draws are of the same sign as the posterior mean.