Abstract

This paper models individual medical care consumption over an insurance year, explicitly accounting for variations in the effective price of medical care due to several characteristics of the health insurance contract. We explain behavior during the health insurance year by solving and estimating a stochastic, discrete choice, dynamic optimization problem that characterizes an individual’s decision to consume care in periods of illness and wellness. The solution provides probabilities of curative and preventive treatment, of illness, of medical care charges, and of health insurance plan choice. Using the estimated structural parameters of the individual’s optimization problem we are able to predict behavior under alternative cost-sharing provisions of endogenous health insurance contracts.

Key Words: Medical care use, health insurance, moral hazard, adverse selection.
1 Introduction

A mutually dependent relationship between individual health insurance decisions and medical care utilization is quite evident. On one hand, health insurance and, in particular, the characteristics of one’s health insurance plan influence the consumption of medical care. On the other hand, one’s expected medical care utilization and expenditures influence the decision to purchase health insurance and the choice among different insurance plans. Despite the intuitive understanding of this relationship (with the first economic discussion by Arrow in 1963 (Arrow, 1963)), there has been relatively little empirical work that accurately, and completely, accounts for both influences on the decision-making behavior of the individual.

The focus of this paper is on the dynamic behavior of individuals during the insurance accounting year in an effort to understand how the parameters of an insurance plan affect decisions throughout the year. In particular, we model the endogenous effects of the health insurance decision (and its corresponding cost-sharing characteristics) on the medical care consumption decisions during the insurance year and vice versa. An analysis of daily, weekly, or monthly consumption behavior may capture the dynamic effects of the insurance plan characteristics better than analyses of annual observations which are prevalent in the literature. These smaller units of observations are necessary to explain the effects of insurance characteristics, such as annual deductibles or maximum out-of-pocket limits, that allow changing marginal prices of care over time. This framework has been applied to the analysis of unemployment insurance, and may be applied similarly to absenteeism behavior, use of vacation days, or welfare participation (given the introduction of policies that limit the length of time one may be enrolled).

Our work also models explicitly the unobserved heterogeneity prevalent in health behaviors. The first concern is accurately allowing for adverse selection. That is, individuals with more information about their health and hence, their health care needs, will self-select into plans best suited for them. Similarly, individuals have private information about their willingness or desire to seek professional medical help which influences their choice of health insurance coverage as well as their medical care utilization during the insurance coverage period. A second concern is that of moral hazard. Once insured, an individual may be more
likely to engage in the behavior for which she is insured; that is, she may be more likely to incur expenses for medical treatment, either by seeking care more frequently, by consuming more care per visit, or by consuming higher priced care. Our model will speak directly to issues of adverse selection and moral hazard in health care behavior.

This work is a first attempt in the health care literature to model and estimate the mutually-dependent demand for health insurance and health care in a sequential discrete choice dynamic framework and to account explicitly for the dollars remaining in one’s deductible at periods shorter than one year. We discuss where the literature stands with regard to this issue in Section 2. Section 3 details the theoretical model that captures health insurance and health care decision-making behavior. In Section 4 we discuss the data used to estimate the model. Section 5 discusses implementation of model solution and estimation given the data limitations. Finally, preliminary estimation results, extensions of the model, and possible policy experiments are discussed in Section 6.

2 Background

The demand for medical care was initially studied as a derived demand from the demand for health itself. Grossman (1972) proposed a deterministic, lifetime utility maximization model in the spirit of Becker’s (1960) household production framework. Medical care is an input to the health production function where health is both a consumption good and an investment good. With these two roles, medical care provides utility today while also having an impact on one’s future utility by determining health transitions and length of life. Early extensions to Grossman’s model provided more realistic behavioral interpretations, but initiated very few empirical investigations of its validity. Most of the empirical demand for health care analyses that appear in this literature, while loosely based on Grossman’s theoretical model, treat health insurance as exogenous. That is, the presence of health insurance or, in a few cases, broad characteristics of health insurance plans such as various cost-sharing measures, define an independent variable of a reduced form regression explaining medical care use.

In 1974 the federal government commissioned an economic experiment where consenting individuals were randomly assigned health insurance plans and their medical care
consumption behaviors were recorded over a three to five year period. Studies based on data from the RAND Health Insurance Experiment (HIE) claim to produce unbiased estimates of the price (or insurance) and income elasticities of medical care demand because insurance can be treated as exogenous. (Sample participation, however, may induce other selection biases.) Even today, much of the accepted wisdom regarding these elasticities is based on results generated by the researchers associated with the RAND HIE (Newhouse, 1993).

With the emergence of other data sets in which health insurance was not randomly assigned, but rather chosen, attempts were made to model the endogenous purchase of health insurance and subsequent medical care use decisions. Cameron, et al. (1988) propose a two period model where insurance is chosen in the first period and medical care is chosen in the second period. The theoretical model correctly accounts for the effects of each decision on the other. In particular, the individual optimally chooses health insurance in the first period by integrating over uncertain future illness states that influence the utility of second period medical care choices. The empirical analysis, however, reduces to an instrumental variables approach to explain observed insurance status and subsequent medical care use. This work characterizes much of the work (and its limitations) on this subject. Namely, the insurance decision does not explicitly account for uncertain future health or medical care use, and the analysis of medical care use depends only on a measure of insurance status, rather than insurance characteristics.

There have been some exceptions regarding measurement of the role of various insurance characteristics. Feldman, et al. (1989) include the degree of medical provider choice associated with employer-provided insurance coverage as a characteristic determining plan choice, along with cost-sharing characteristics such as the level of outpatient and inpatient deductible, coinsurance rate, and annual maximum out-of-pocket expense. To proxy expected medical care utilization they include a dummy variable indicating whether the plan provides coverage for preventive care. Harris and Keane (1999) combine data on plan characteristics, such as premium, coverage, provider choice, and claim submission procedures, with data reflecting attitudes toward plan characteristics to obtain estimates of consumers’
preferences for and perceptions of the attributes of health insurance alternatives. Both analyses, however, are limited to plan choice, and do not evaluate the influence of these plan characteristics on medical care use.

Much of the research explaining the demand for medical care employs annual measures of medical care utilization or expenditures. These annual measures are prevalent in the health care literature, partially due to data limitations. Some of the RAND researchers recognized that common features of health insurance plans result in non-linear prices of care during the insurance accounting period: deductibles and maximum out-of-pocket amounts (Keeler, Newhouse, and Phelps, 1977). Depending on the provisions of one’s health insurance plan, the price faced for medical treatment changes as one consumes care. For example, an individual may have a health insurance plan that specifies a $200 annual deductible and a 20% coinsurance rate (or out-of-pocket percentage) on all purchases after the deductible has been exceeded. The price of the first medical service encounter is likely to be 100% of the total charge. After consuming some care, paying the cost, and reducing the amount remaining before exceeding his deductible, the perceived (or effective) price of future services falls below the actual price charged. They suggest that analysis of behavior over episodes of illness, rather than that of annual behavior, will allow for correct measurement of the price responsiveness of medical care demand when deductibles characterize the cost-sharing arrangements associated with health insurance. This smaller unit of analysis will allow a researcher to control for time remaining in the insurance accounting period as well as (monetary) distance to the price change associated with the deductible (or maximum out-of-pocket amount). Despite this charge to empirical health economists almost four decades ago, such a model has not been estimated.

Gilleskie (1998) furthered the effort to understand medical care utilization, and in particular, physician visits, by modeling individual daily decisions to visit a physician and/or to be absent from work during an episode of illness. Using data from the 1987 National Medical Expenditure Survey which provides dates for all medical encounters, Gilleskie develops

\[\text{1}\] Also see Ellis (1984) and Ellis and McGuire (1986) for a similar discussion of the cost-sharing characteristics of health insurance for mental health care. The empirical model in each of these papers, however, does not account for the dynamic consequences of insurance characteristics during the year.
a model of a worker’s daily decision-making behavior over an episode of acute illness that account explicitly for the uncertainty associated with contraction of illness and recovery from illness. While this study disaggregates the many decisions and sources of uncertainty bundled up in annual measures, it does not account for changes in the effective price of medical care over an insured individual’s insurance accounting year. That is, the dynamic responses of individuals to changes in prices of care (determined by plan characteristics and past individual choices) cannot be determined.

A review of the relevant health economics literature illustrates the theoretical and pedagogical relevance of modeling the effects of the cost-sharing characteristics of insurance plans on the demand for care, as well as the effects of expected utilization on the demand for different cost-sharing characteristics. It is also interesting from a policy perspective to quantify these effects. Recently health economists have been called upon to explain the upward-spiraling costs of health care in the United States. The major factors appear to be those beyond the control or influence of health policy makers, such as population increases, general inflation, and demographic changes (e.g., aging), and those within the realm of health policy control, such as medical care inflation, changes in utilization per person, and changes in intensity of services per person. These latter changes may reflect changes in technology, malpractice, regulation, or insurance practices. While a model that explicitly accounts for each of these factors is ideal, our model focuses on the partial equilibrium behavior of individuals with regard to medical care utilization and insurance purchase.

In the past 40 years, health care spending as a percent of our gross domestic product (GDP) has increased from 5.3% in 1960 to 14.9% in 2002. Over this same period, the out-of-pocket responsibility of individuals for personal health care expenses has fallen from 55.9% to 15.9% (See Figure 1). While a one-to-one tradeoff certainly does not exist, it seems reasonable to study the effects of third party payers on the utilization of medical care. Can we quantify the moral hazard effects of decreased cost sharing among consumers of medical care? How is medical care consumption influenced by alternative cost-sharing arrangements?
Figure 1: National Health Expenditures and Out-of-Pocket Payments

3 The Model

The model detailed below describes an individual’s optimization behavior over a lifetime with regard to medical care consumption and health insurance purchases. It explains the sequential decision-making process that one faces when both illness and prices of treatment are uncertain. The model explicitly accounts for variation in the effective price of medical care during an insurance year due to the characteristics of one’s chosen insurance policy and accumulated medical care expenditures. It also describes the choice among insurance plans as a function of optimal future medical care consumption behavior. The primary focus of this research is accurately modeling behavior induced by the changing nature of the budget constraint.

The dynamic stochastic model captures the sequential decision-making behavior of individuals by modeling insurance choices each year and medical care utilization decisions from the day their medical insurance begins throughout the insurance year. These medical care decisions depend on previous events during the year and expected medical care utilization in the future. At each discrete period an individual faces a probability of being well or of being sick. The probability is a function of past preventive medical care use and past illness as well as individual characteristics. If the individual is well, then he may choose to consume preventive medical services or not. If he is ill, then he may choose to consume curative medical care or not. His utilization decision depends on the distribution of prices of that particular type of care because prices are not observed at the point of decisionmaking. Each type of care (curative and preventive) requires payment dependent on characteristics of the individual’s insurance plan, which is chosen annually.
The model is restricted to individuals who are full-time, full-year employees. The insurance alternatives are limited to single coverage insurance plans. We restrict analysis to this type of plan, and do not include family coverage plans, in order to avoid modeling each family member’s consumption of medical care and their probabilities of illness. Labor force participation decisions and job changes are not modeled. All parameters of the structural model described below are estimated simultaneously.

3.1 Per-period Discrete Choices

Prior to making decisions about medical care consumption, an individual must choose a health insurance plan or be uninsured. Health insurance plans are characterized by a deductible amount, $D$; a coinsurance percentage, $C$; and a maximum deductible expenditure, $M$. Deductibles range from $100 to $350 in $50 increments. Coinsurance percentages range from 0% out-of-pocket responsibility to 30% out-of-pocket responsibility in 10 percentage point increments. Maximum deductible expenditure amounts are $1000, $2000, $2500, and $5000. Each combination of insurance characteristics defines a health insurance plan denoted $i, i = 1, \ldots , I$. An indicator variable, $d_{ia}$, indicates that health insurance plan $i$ is chosen at the beginning of year, $a$; $i = 0$ indicates that the individual has chosen to be uninsured.\footnote{We assume, in this version of the paper, that each combination of insurance characteristics is available to all individuals. We will explore different assumptions in the future.}

The cost of each insurance plan also affects the insurance decision. We allow health insurance premiums to differ across plans, but not across people within plans. We do not consider plan differences characterized by coverage of different services or degree of provider choice.

In each period individuals may occupy one of two distinct health states indicated by the variable $h_t$: well in period $t$ ($h_t = 0$) or sick in period $t$ ($h_t = 1$). An individual faces different decisions when well than when ill. The alternatives available to an individual who is well are whether to seek preventive treatment or not. The alternatives available to an
individual who is ill are whether to consume curative treatment or not. The alternatives are summarized by an indicator function, $d_{ht}^j$, that indicates which alternative $j$ is chosen in health state $h$ of period $t$. More specifically, the medical care alternatives are

\[
\text{if } h_t = 0, \text{ then} \quad j = 0 : \text{do not consume preventive care} \\
\quad j = 1 : \text{consume preventive care,}
\]

and if $h_t = 1$, then

\[
\text{if } h_t = 1, \text{ then} \quad j = 0 : \text{do not consume curative care} \\
\quad j = 1 : \text{consume curative care.}
\]

### 3.2 History of Health and Health Behavior

The decisions made at the beginning of each year $a$ and during period $t$ of the current calendar year, $(t = 1, \ldots, T_a)$, depend on the individual’s health history and his health behavior up to period $t$. This history determines the “state” at which an individual enters a new period. The state at the beginning of period $t$, denoted $Z_t$, is a vector composed of the following variables: the health state in the previous period, $h_{t-1}$; an indicator of whether the individual has had any preventive visits (during this current insurance year) up to period $t$, $v_t$; and the deductible remainder (i.e., dollars until the deductible is passed) at the beginning of period $t$, $r_t$.

The laws of motion, or evolutions, of the state variables determine the values of the state space in all periods. The time period $t = 0$ refers to the instantaneous “period” in which an insurance plan is chosen. The dollars remaining in the deductible decreases with an individual’s out-of-pocket payments for medical care. The variable $D_t$ denotes an individual’s

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$^3$The letter $h$ is used as a superscript as well as a state variable. In either context they indicate the health state of an individual in period $t$. 

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deductible level in dollars associated with insurance plan \( i \). The variable \( \tilde{p}_t \) denotes the individual’s out-of-pocket expenditure on medical care in period \( t \) if he consumes preventive care when well or curative care when ill (as indicated by \( d_{t-1}^{h_1} \)). The dollars remaining in one’s deductible follow

\[
    r_t = \begin{cases} 
        r_{t_{a-1}+1} & t = 0 \\
        D_i & t = 1 \\
        \max(0, r_{t-1} - \tilde{p}_{t-1} d_{t-1}^{h_1}) & t = 2, \ldots, T_a 
    \end{cases}
\] (1)

We keep track of the remainder at the end of the previous health insurance year because it may influence the health insurance choice for the current year. As indicated, the dollars remaining in one’s deductible reinitializes to \( D_i \) at the start of each insurance year.

These variables define the information available to an individual at the beginning of period \( t \), \( Z_t = (h_{t-1}, v_t, r_t, H_t^*) \), where \( H_t^* \) denotes observed and unobserved (to the researcher) individual health-related, demographic, and economic characteristics, and includes past preference shocks defined in Section 3.4.

### 3.3 Illness Probabilities

The illness probability, denoted \( \pi_t \), defines the probability that an individual will be ill during period \( t \). It is a logistic function of the health state of the individual at time \( t - 1 \); his use of preventive care up to time \( t \), \( v_t \); and a vector of observed and unobserved characteristics of the individual, \( H_t^* \). This vector contains observed individual health-related, demographic, and economic characteristics, \( H_t \), such as health status, age, gender, and income as well as unobserved heterogeneity which we discuss in more detail in Section 5. The probability a person is ill in time \( t \) is

\[
    \pi_t(Z_t) = \frac{\exp(\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 v_t + \gamma_3' H_t^*)}{1 + \exp(\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 v_t + \gamma_3' H_t^*)}.
\] (2)
It is implicitly assumed that the probability of recovery at the end of a period of illness is one. However, an individual may be ill for consecutive periods. The illness probability can be made more general by assuming an ill health state characterized by differing severity levels $s$. In this case, the estimated parameters of $\pi_t(\cdot)$ would be severity subscripted, with an additional assumption about the distribution of illness severities. Henceforth, we drop the arguments of $\pi_t(\cdot)$ for notational simplicity.

3.4 Per-period Utility Function and Budget Constraint

Per-period utility is a function of an individual’s consumption of a composite good denoted $X_t$, the health care alternatives, and her observed health state $h$ in period $t$. The utility (or disutility) one receives from seeking treatment may capture the alleviated pain, psychic happiness, or physical discomfort one feels from consuming health care. The health state influences the marginal utility of consumption, as well as the utility from different types of treatment. Utility is also a function of an unobserved taste shifter, $\phi_{hj}^t$, for each alternative $j$ in each health state $h$ and time period $t$. The value of this component is unobserved by the econometrician but known by the individual at the beginning of the period. The per-period utility function, conditional on the chosen health insurance coverage characteristics, is

$$U^h(X_t, d_t^h, \phi_{hj}^t | d_a^h) = \alpha_{h0} + \frac{X_t}{\alpha_{h1}} + \alpha_{h2}d_{h1}^t + \alpha_{h3}d_{01}^t \cdot v_t + \alpha_{h4}H_t + \sum_{j=0}^{1} \phi_{hj}^t d_{i}^{bj}, \quad \forall h, \forall j, \forall t. \quad (3)$$

A person’s utility is constrained by his budget which is determined by his per-period income $Y_t$, his consumption of the composite consumption good and medical care, and the parameters of his health insurance plan. The price of the consumption good is normalized to one. The variable $\hat{p}_t$ denotes the out-of-pocket price of medical care treatment and is determined by the total charge for medical services during period $t, p_t'$; the dollars remaining in one’s deductible at time $t, r_t$; and the coinsurance rate, $C_i$ associated with insurance plan
However, the total cost of treatment is unknown prior to making the utilization decision. The superscript $\ell$ on the total charge captures variation in the price of medical services. More specifically, the budget constraint is

$$X_t = Y_t - \hat{p}_t(p^\ell_t, r_t, C_i) d^h_i, \quad \forall \ell$$

(4)

where,

$$\hat{p}_t(p^\ell_t, r_t, C_i) = \begin{cases} 
  p^\ell_t & \text{if } p^\ell_t \leq r_t \\
  r_t + (p^\ell_t - r_t)C_i & \text{if } 0 < r_t < p^\ell_t \\
  p^\ell_tC_i & \text{if } r_t = 0.
\end{cases}$$

(5)

If prices are continuous, we could specify the distribution of total costs of treatment with a one or two parameter distribution, such as log normal or Pareto, and obtain expected utility by integrating. However, charges influences out-of-pocket costs which influence the dollars remaining in the deductible. In an effort to avoid continuous state variables, we express prices (or total costs) in dollar units (e.g., $25 increments) and assume a discrete distribution of charges. Thus, an expectation of future utility requires a summation over probability-weighted charges rather than integration over a continuous distribution. The charge distribution must be explicitly accounted for in order to capture the dynamics resulting from deductibles and maximum deductible expenditure amounts. However, once an individual has passed his deductible and faces medical care prices scaled by his coinsurance rate, different prices for medical care affect only his current period utility (in the case where there is no MDE). The discrete distribution of prices follows a mixed logit specification where

$$\lambda_{h\ell} = \frac{\exp (\xi_{h\ell 0} + \xi_{h\ell 1}^0 H_t^* + f(\xi, \ell))}{1 + \sum_{\ell' = 1}^L \exp (\xi_{h\ell 0} + \xi_{h\ell 1}^{\ell'} H_t^* + f(\xi, \ell))}, \quad \ell = 1, \ldots, L$$

(6)

where

$$f(\xi, \ell) = \left(\xi_{h2}\ell + \xi_{h3}\ell^2\right) L_1 + \left(\xi_{h4}(\ell - \ell_1) + \xi_{h5}(\ell - \ell_1)^2\right) L_2$$

$$+ \left(\xi_{h6}(\ell - (\ell_1 + \ell_2)) + \xi_{h7}(\ell - (\ell_1 + \ell_2))^2\right) L_3$$

(7)
and

\[ L_1 = \begin{cases} 
1 & \text{if } \ell \leq \ell_1 \\
0 & \text{otherwise}
\end{cases} \]

\[ L_2 = \begin{cases} 
1 & \text{if } \ell_1 < \ell \leq (\ell_1 + \ell_2) \\
0 & \text{otherwise}
\end{cases} \]

\[ L_3 = \begin{cases} 
1 & \text{if } \ell > (\ell_1 + \ell_2) \\
0 & \text{otherwise}
\end{cases} \]

The variables $\ell_1$ and $\ell_2$ are defined in terms of the dollar units and the maximum deductible among all insurance plans.

### 3.5 The Conditional Utilization Decisions

Conditional on his health insurance this year, $d_a$, the objective of an individual is to choose whether or not to consume preventive and curative medical services so as to maximize the period $t$ value of his discounted lifetime expected utility. The function $V^h_j(\cdot)$ denotes expected lifetime utility of an individual choosing alternative $j$ in health state $h$. Specifically, the value function at $t$, conditional on the medical care charge $p_t^\ell$ and insurance plan $i$, is

\[
V^h_j(Z_t, \phi^h_t | p_t^\ell, d_a) = U^h_j(X_t) + \phi^h_j
\]

\[
+ \beta \left[ \pi_{t+1} V^1(Z_{t+1} | d_a^i) + (1 - \pi_{t+1}) V^0(Z_{t+1} | d_a^i) \right], \quad t < T .
\]

The individual’s optimization problem is solved recursively backwards. In the last time period of the year, when an insurance decision will be made in the following time period, the conditional value function is

\[
V^h_j(Z_T, \phi^h_T | p_T^\ell, d_a) = U^h_j(X_T) + \phi^h_j + \beta W_{a+1}(Z_0), \quad \forall h, \forall j, \forall a, t = T
\]
where $W_{a+1}(\cdot)$ represents the value of future utility at the beginning of the next year when the individual makes another insurance decision. This value is defined in section 3.6 below. Unconditional on the charge, the value function becomes

$$V_h(z_t'|d_a') = \sum_{\ell=0}^{L} \lambda_h^\ell V^h_j(z_t', \phi^h_t|p^{d_t}_\ell, d_a'), \quad \forall t, \forall h, \forall j. \quad (10)$$

The maximal expected value of utility in health state $h$ and time period $t$, conditional on health insurance but unconditional on the preference shocks $\phi^h_t$, is

$$V^h(z_t|d_a') = E_{t-1} \left[ \max_j V^h_j(z_t', \phi^h_t|d_a') \right], \quad \forall h, \forall t. \quad (11)$$

An important point here is that the individual makes a decision about medical care utilization before he knows the charge for the services. This assumption captures that fact that people do not know exactly what the charge will be prior to treatment because prices are not advertised, there may be possible complications, and the doctor may require additional tests. Additionally, modeling the charge distribution and allowing it to differ according to observed and unobserved characteristics of the individual enables us to describe the behavior of individuals for who choose not to seek care, and thus no charge is observed.

### 3.6 The Annual Insurance Decision

At the beginning of each year, an individual chooses a health insurance plan for the following year. This decision depends on the individual’s health-related characteristics, his expected utilization or value of utility for the upcoming year, illness in the previous period, preventive care during the previous year, and the remainder in his deductible at the end of the previous year. From above, the expected discounted present value of utility in period one, conditional on insurance plan $i$ and on the realized health state, $h$, is $V^h(z_t|d_a')$. Weighted by the probability of being ill, which is unknown prior to the beginning of $t (=1)$, the expected
value of utility next year conditional on a specific insurance plan is

\[
V(Z_0|d_a^i) = \left[ \pi_1 V^1(Z_1|d_a^i) + (1 - \pi_1) V^0(Z_1|d_a^i) \right].
\]  

(12)

The vector \( \phi_a = (\phi_a^0, \ldots, \phi_a^I) \) represents unobserved heterogeneity that may affect an individual’s health insurance decision. The value of utility of a particular insurance alternative \( i \) during the decision period \( a \) (where \( t = 0 \)), denoted \( W^i_a(\cdot) \), is

\[
W^i_a(Z_0, \phi_a) = \nu_{0i} + \nu_1 V(Z_0|d_a^i) + \phi_a^i \quad \forall a, \forall i.
\]  

(13)

The expected lifetime utility at the beginning of period \( a \) is

\[
W_a(Z_0) = E_{T_{a-1}+1} \left[ \max_i W^i_a(Z_0, \phi_a) \right].
\]  

(14)

This value of utility prior to the health insurance decision defines future utility in period \( T_a \) (Equation 9).

4 Description of the Data

Empirical analysis of the effects of cost sharing (or characteristics of a health insurance plan) requires units of observation smaller than the period of coverage by the insurance plan. Most health insurance plans insure against the high cost of care for one year, and are renewable. The 1987 National Medical Expenditure Survey (NMES) provides the most current and most disaggregated data for capturing changes in the effective price of medical treatment over an individual’s insurance year. The NMES data detail every medical event (illness and medical care consumption) of an individual during the 1987 calendar year. Charges and payments by all payers are available.\(^4\) By knowing the dates of a person’s illness episode, the dates of

\(^4\)It also contains detailed information on health status, health insurance coverage, employment, income, and demographics, although many of these variables are annual or one-time observations.
medical care use, and the characteristics of his health insurance plan, we can determine how much an individual has remaining in his deductible at every period of decision making.

The main drawback of the NMES data set is that the survey covers only one year. The NMES data provide detailed information on medical care consumption over the 1987 calendar year, but do not follow individuals for many years. With the appropriate data, mainly observations of individual insurance purchases over many years, one may better be able to quantify the influence of adverse selection as changes in health status over time might also be observed. However, current data sets that collect information on insurance decisions over time do not contain enough information to account explicitly for dynamic (during the year) changes in the prices of medical care due to insurance characteristics.

4.1 Determination of the Sample

The sample used to estimate the model of consumption behavior consists of males and females age 25 to 64 who reported being employed each of the interview rounds. In order to avoid modeling endogenous employment decisions or exogenous work separations, we select only full-time, full-year employed individuals for our analysis. Similarly, because the focus of this paper is on understanding the effects of dynamic changes in prices of medical care induced by one’s insurance plan and his utilization, we limit the sample to individuals with single coverage insurance policies. This restriction allows us to model individual, rather than family, decisions. However, individuals in the sample may be married or single. Because observations are available for one year beginning January 1, 1987, we choose individuals with insurance plans that list January as the first month of coverage. Finally, if an individual has more than one source of insurance coverage, he or she is dropped from our sample. Our sample contains 686 individuals. Because specific calendar dates are associated with the illness and utilization data, we could, theoretically, model daily behavior during the
year. However, computational difficulty in solution and estimation, as well as some missing dates, require that we lengthen the decision period. In the current version of the model, we model monthly treatment decisions and one annual health insurance decision. Thus, we use 8918 (= 686 × 13) person observations in estimation. Table 1 details the sample selection information.\footnote{In this version of the paper, the sample does not include uninsured individuals. A more recent selection of the data that includes those without health insurance coverage yields 1043 individuals.}

<table>
<thead>
<tr>
<th>Table 1: Sample Selection Information</th>
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<tbody>
<tr>
<td><strong>Total Number of Observations</strong></td>
</tr>
<tr>
<td>age 25-64, employed full time, full year</td>
</tr>
<tr>
<td>with completed Health Status Questionnaire</td>
</tr>
<tr>
<td>and valid responses to relevant variables</td>
</tr>
<tr>
<td>and only one source of single coverage insurance</td>
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<td>and valid insurance information</td>
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4.2 Description of the Sample

Health Insurance Plans

The NMES survey provides detailed information about an individual’s health insurance plan. The data include indicators of coverage for a complete breakdown of services and procedures and specifics about the third party payment for each service or procedure. More specifically, we have information about deductibles, coinsurance rates, maximum deductible amounts, and maximum coverage limits for each type of covered service. While this information allows for an almost exact record of the effective price of treatment over a year, it is too thorough for many analyses of health insurance effects due to the complexity of most insurance plans. (There are more combinations of these characteristics than there are people in
the survey sample.) We have chosen to focus on deductibles, coinsurance rates, and maximum deductible amounts as key cost-sharing characteristics of plans. We also focus on the most frequently covered services such as physician office visits, outpatient hospital care, emergency room visits, inpatient hospital stays, and prescribed medicines. We ignore consumption of routine vision and dental care because most plans do not cover these expenses or people have separate plans for these services. We also exclude home health care and medical device expenses.

Figure 2 displays the distribution of deductible values and coinsurance rates of the covered services of interest in our sample. Figure 3 shows the most common combinations of deductibles and coinsurance rates. In an effort to reduce the number of health insurance alternatives in our preliminary analyses, we group plans into four categories that define the discrete health insurance alternatives: a $100 deductible and a 10% coinsurance rate, a $100 deductible and a 20% coinsurance rate, a $200 deductible and a 20% coinsurance rate, and a $300 deductible and a 20% coinsurance rate. The sample proportions in each discrete plan are 7%, 41%, 35%, and 17%, respectively.

Illness

We determine whether an individual is ill or not in a specific period by using episode information from the NMES data. The survey reports beginning and ending dates of illnesses during the year.6 Most illness episodes specify a beginning and ending date within the 1987 calendar year. We assume that those illnesses that are first noticed prior to 1987 and continue throughout 1987 are chronic illnesses. Chronic illnesses include those with a long duration (e.g., heart disease, asthma, diabetes) and those that occur frequently over a long

---

6An individual is observed to have any illness only if he sought treatment at least once or missed work at least once during the episode of illness. A correction for this censoring of the data should be included in construction of the likelihood function (Gilleskie, 1998).
period of time (e.g., migraines and hay fever). We believe that people with chronic illnesses behave differently with regard to medical care consumption because they expect acute flare-ups of their illness and anticipate treatment in the future. They are more likely to consume preventive care in relation to their chronic illness. In our sample, 42% have at least one chronic illness. We account for other illnesses, such as influenza, in modeling the observed behavior of individuals with chronic illness. The top panel of Figure 4 depicts the probability of non-chronic illness on each day of the calendar year. It appears that individuals are more likely to be ill at the end of the year than at the beginning given the nearly monotone feature of the probability over time. However, it is possible that a person becomes ill and does not report a recovery date within the observed calendar year. It may be the case that the person has contracted a chronic illness which they will have for a long time, or that they simply

Figure 2: Distribution of Deductibles and Coinsurance Rates
Figure 3: Combinations of Deductibles and Coinsurance Rates

Note: Radii of circles denote the relative frequency of the deductible/coinsurance combination at the center of the circle.
have not recovered by the end of 1987. Alternatively, the bottom panel of Figure 4 displays the probability that a specific day of the year is the first day of a new illness.\footnote{Efforts are being made currently to identify contraction of chronic illness during the year and to more accurately determine ending dates of all illnesses. This information is expected to decrease the proportion of ill individuals in the latter part of the year in the top panel graph of Figure 4.}

**Medical Care Consumption**

While an analysis of dynamic medical care consumption over an entire year should account for decisions to purchase medical care disaggregated into various types of services, we found this task to be overwhelming in our initial undertaking of the project. Consequently, we do not differentiate expenditures on different types of services. We also divide the year into discrete periods.\footnote{In this version of the paper each discrete period is one month. Although it may be computational infeasible to reduce the period length to one day, we are experimenting with biweekly and weekly periods.} We determine whether an individual is ill or well each period based on dates of his illness episodes. We also distinguish between illnesses that are chronic and acute. Given this assignment of ill and well periods we then assign the medical care consumption of an individual to specific periods. We assume that an individual consumes curative care only when ill and preventive care only when well. We consider care sought for chronic illnesses as preventive care. For example, a person with hay fever may receive allergy shots from a physician regularly. Persons with heart disease or high blood pressure may have periodic visits to the physician for surveillance. Figure 5 depicts the monthly curative treatment behavior of individuals in the sample; Figure 6 displays the monthly preventive treatment behavior.

**Charges for Medical Care Treatment**

Charges for curative treatment and preventive treatment are very different, as indicated in Table 2. An example of the entire charge distribution for curative care is depicted in Figure 7. Notice that charges of zero dollars occur with a non-zero probability.
Figure 4: Illness Probabilities

Note: Probability on y-axes.
Figure 5: Monthly Curative Care Utilization conditional on being ill

Note: Probabilities of seeking care on y-axes.
Figure 6: Monthly Preventive Care Utilization conditional on being well
Figure 7: Distribution of Charges for Curative Treatment
Table 2: Distribution of Monthly Charges for those Seeking Care

<table>
<thead>
<tr>
<th>Treatment Sample</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curative</td>
<td>0</td>
<td>19117</td>
<td>376.61</td>
<td>1355.07</td>
<td>60</td>
</tr>
<tr>
<td>Preventive</td>
<td>0</td>
<td>13687</td>
<td>261.95</td>
<td>1142.06</td>
<td>50</td>
</tr>
<tr>
<td>Curative, No Chronic Illness</td>
<td>0</td>
<td>12495</td>
<td>284.87</td>
<td>1055.13</td>
<td>50</td>
</tr>
<tr>
<td>Preventive, No Chronic Illness</td>
<td>0</td>
<td>1200</td>
<td>89.60</td>
<td>140.49</td>
<td>50</td>
</tr>
<tr>
<td>Curative, With Chronic Illness</td>
<td>0</td>
<td>19117</td>
<td>451.81</td>
<td>1555.44</td>
<td>70</td>
</tr>
<tr>
<td>Preventive, With Chronic Illness</td>
<td>0</td>
<td>13687</td>
<td>291.67</td>
<td>1232.93</td>
<td>50</td>
</tr>
<tr>
<td>Curative, Pass Deductible</td>
<td>0</td>
<td>19117</td>
<td>472.71</td>
<td>1495.44</td>
<td>66</td>
</tr>
<tr>
<td>Preventive, Pass Deductible</td>
<td>0</td>
<td>13687</td>
<td>334.57</td>
<td>1309.14</td>
<td>60</td>
</tr>
<tr>
<td>Curative, Do Not Pass Deductible</td>
<td>0</td>
<td>13497</td>
<td>240.99</td>
<td>1115.40</td>
<td>50</td>
</tr>
<tr>
<td>Preventive, Do Not Pass Deductible</td>
<td>0</td>
<td>10376</td>
<td>188.21</td>
<td>938.58</td>
<td>36</td>
</tr>
</tbody>
</table>

Note: Calculations include treatments with zero charges.

Observed Individual Heterogeneity

We summarize the observed heterogeneity of individuals in the sample by gender, age, self-reported health status, chronic illness, and labor income. We discretize age into two 20-year intervals: 25 to 44 and 44 to 65 years of age. Health status is either excellent, good, or fair/poor. Individuals may have at least one chronic illness or have no chronic illnesses. Income categories are lower income, middle income, and upper income, defined by the monthly income intervals ($300, $1800), [$1800, $2700), and [$2700, +), respectively. Table 3 presents proportions of each observed type by gender and reports means and standard deviations of relevant variables. Table 4 displays the sample size according to observed characteristics.
### Table 3: Proportion and Moments by Selected Groups

<table>
<thead>
<tr>
<th>Group</th>
<th>Males</th>
<th></th>
<th></th>
<th>Females</th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Prop</td>
<td>Mean</td>
<td>StDev</td>
<td>Prop</td>
<td>Mean</td>
<td>StDev</td>
<td></td>
</tr>
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<td>Health Status</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Excellent</td>
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<td>0.30</td>
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<td>0.30</td>
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<td>Good</td>
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<td>0.56</td>
<td></td>
<td>0.56</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Fair/Poor</td>
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<td>0.14</td>
<td></td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Income</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>Lower Income</td>
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<td>1009</td>
<td>251</td>
<td>0.27</td>
<td>1005</td>
<td>236</td>
<td></td>
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<td>Middle Income</td>
<td>0.48</td>
<td>1981</td>
<td>344</td>
<td>0.53</td>
<td>1887</td>
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<td>Upper Income</td>
<td>0.33</td>
<td>4093</td>
<td>1422</td>
<td>0.20</td>
<td>3592</td>
<td>898</td>
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<td>Age</td>
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<tr>
<td>25-44 Years</td>
<td>0.71</td>
<td>32.23</td>
<td>5.32</td>
<td>0.61</td>
<td>33.13</td>
<td>5.63</td>
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<tr>
<td>45-64 Years</td>
<td>0.29</td>
<td>53.43</td>
<td>5.51</td>
<td>0.39</td>
<td>54.74</td>
<td>5.40</td>
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<tr>
<td>Race</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Hispanic</td>
<td>0.07</td>
<td>0.07</td>
<td></td>
<td>0.07</td>
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<tr>
<td>Black</td>
<td>0.17</td>
<td>0.20</td>
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<tr>
<td>Other</td>
<td>0.76</td>
<td>0.73</td>
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<td>0.73</td>
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<td></td>
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<td>Marital Status</td>
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<tr>
<td>Married</td>
<td>0.45</td>
<td>0.47</td>
<td></td>
<td>0.47</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Single</td>
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<tr>
<td>Health Insurance</td>
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<td></td>
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<tr>
<td>($100, 10%)</td>
<td>0.07</td>
<td>0.07</td>
<td></td>
<td>0.07</td>
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<td></td>
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<tr>
<td>($100, 20%)</td>
<td>0.39</td>
<td>0.42</td>
<td></td>
<td>0.42</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>($200, 20%)</td>
<td>0.35</td>
<td>0.34</td>
<td></td>
<td>0.34</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>($300, 20%)</td>
<td>0.19</td>
<td>0.16</td>
<td></td>
<td>0.16</td>
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<td></td>
<td></td>
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<tr>
<td>Curative Treatment Visits</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>per year</td>
<td>1.00</td>
<td>2.03</td>
<td>4.70</td>
<td>1.00</td>
<td>3.08</td>
<td>6.30</td>
<td></td>
</tr>
<tr>
<td>per year&gt; 0</td>
<td>0.42</td>
<td>4.85</td>
<td>6.38</td>
<td>0.59</td>
<td>5.23</td>
<td>7.49</td>
<td></td>
</tr>
<tr>
<td>Preventive Treatment Visits</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>per year</td>
<td>1.00</td>
<td>2.26</td>
<td>8.30</td>
<td>1.00</td>
<td>2.11</td>
<td>4.45</td>
<td></td>
</tr>
<tr>
<td>per year&gt; 0</td>
<td>0.33</td>
<td>4.85</td>
<td>13.35</td>
<td>0.49</td>
<td>4.35</td>
<td>5.57</td>
<td></td>
</tr>
<tr>
<td>Preventive Treatment Visits (no chronic illness)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>per year</td>
<td>0.65</td>
<td>0.17</td>
<td>0.67</td>
<td>0.52</td>
<td>0.66</td>
<td>2.39</td>
<td></td>
</tr>
<tr>
<td>per year&gt; 0</td>
<td>0.12</td>
<td>1.50</td>
<td>1.37</td>
<td>0.26</td>
<td>2.55</td>
<td>4.19</td>
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<tr>
<td>Illness</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Non-Chronic Illness</td>
<td>0.58</td>
<td>0.69</td>
<td></td>
<td>0.69</td>
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<td></td>
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<tr>
<td>Chronic Illness</td>
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<td>0.47</td>
<td></td>
<td>0.47</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Prop measures the proportion of the sample in each group.
Table 4: Sample Sizes by Type

<table>
<thead>
<tr>
<th>Income</th>
<th>Age</th>
<th>Exc</th>
<th>Good</th>
<th>F/P</th>
<th>Exc</th>
<th>Good</th>
<th>F/P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower</td>
<td>25-44</td>
<td>9</td>
<td>19</td>
<td>2</td>
<td>9</td>
<td>27</td>
<td>3</td>
</tr>
<tr>
<td>Middle</td>
<td>25-44</td>
<td>25</td>
<td>43</td>
<td>6</td>
<td>32</td>
<td>40</td>
<td>5</td>
</tr>
<tr>
<td>Upper</td>
<td>25-44</td>
<td>23</td>
<td>13</td>
<td>1</td>
<td>18</td>
<td>19</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>45-64</td>
<td>4</td>
<td>6</td>
<td>1</td>
<td>3</td>
<td>12</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>45-64</td>
<td>4</td>
<td>16</td>
<td>2</td>
<td>14</td>
<td>16</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>45-64</td>
<td>4</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>4</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Income</th>
<th>Exc</th>
<th>Good</th>
<th>F/P</th>
<th>Exc</th>
<th>Good</th>
<th>F/P</th>
</tr>
</thead>
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<tr>
<td>Lower</td>
<td>2</td>
<td>3</td>
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<td>2</td>
<td>13</td>
<td>3</td>
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<td>11</td>
<td>6</td>
<td>3</td>
<td>11</td>
<td>1</td>
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</tbody>
</table>

5 The Estimation Procedure

5.1 Solution of the Optimization Problem

The theoretical model presented in Section 3 applies to decisions made over multiple years. That is, the model allows for changes in health insurance plan choice each year. However, because the data are available for only one year, estimation of the model as specified is impossible. If the data were available to model plan switches, we would want to allow changes in individual characteristics to influence plan choice. For example, treatment and prevention decisions, as well as illness episodes, are likely to affect a person’s health status. Improvements or deterioration in general health may affect an individual’s optimal plan choice. Similarly, changes in marital status, employment status, or family size may also influence plan choice.\(^9\)

In this section we describe how estimation is implemented given the restrictions of the data. The biggest disadvantage of having only one year of data is that we do not know the

\(^9\)Modelling marriage, labor force participation, and fertility decisions is beyond the scope of this paper.
behavior of an individual prior to 1987. Hence, initial conditions such as illness last period (i.e., $T_{a-1}$) and preventive care use in the previous year are unknown, and thus integrated out of the model. Similarly, the remainder in one’s deductible from the previous year, which might influence insurance decisions this year, is not observed and hence not included as a predictor of insurance choice in the estimated model.

More importantly however, it is crucial to account for unobserved heterogeneity that leads to adverse selection and moral hazard. We account for any unobserved information that may influence insurance plan choice as well as decisions to seek preventive and curative medical care by including the components $\phi_a = (\phi_a^1, \ldots, \phi_a^I)$ in the insurance preference function and $\phi_t = (\phi_t^{h0}, \phi_t^{h1})$ in the per-period utility function. We allow these components to be correlated across decisions and across time. More specifically, these components decompose into two additive parts,

$$\phi_a^i = \eta_{ai} \mu + \epsilon_a^i, \quad \forall a, \forall i$$

$$\phi_t^{hj} = \begin{cases} 
\eta_{2j} \mu + \epsilon_t^{0j}, & \text{if } h_t = 0 \\
\eta_{3j} \mu + \epsilon_t^{1j}, & \text{if } h_t = 1 
\end{cases} \quad \forall t, \forall j. \quad (15)$$

The first part, $\mu$, is an individual-specific component that persists across time and across decisions. The second part, $\epsilon$, is uncorrelated across individuals, time, health states, alternatives, and decisions. The $\eta$’s are factor loadings that measure the influence of the heterogeneity everywhere it enters. To be more specific, $\eta_{ai}$ is the factor loading on $\mu$ that measures the effect of $\mu$ on the utility of each insurance alternative. Similarly, $\eta_{2j}$ captures the effect of permanent unobserved individual characteristics on curative treatment decisions; $\eta_{3j}$, on preventive care decisions.
In order to estimate the parameters of the model, distributional assumptions must be made about the unobserved components $\mu$ and $\epsilon$. The random unobserved components, $\epsilon$, are independent and identically distributed Extreme Value errors. Their conditional independence and additive inclusion decrease the computational burden associated with solution of the optimization problem (Rust, 1987). A distribution of the time-invariant individual component of utility, $\mu$, is not assumed. Rather, the continuous unknown distribution is approximated by a step function in the spirit of Heckman and Singer (1984). Mroz and Guilkey (1992) and Mroz (1999) show through Monte Carlo simulations that the discrete factor approximation method produces similar estimates of model parameters when normality is imposed. When the simulated distribution is not normal, this method actually performs better than when normality is assumed. Although the theoretical estimator converges to the true distribution as the number of support points approaches infinity, very few mass points are needed for a good fit.

Given the limitations of the data, as well as the more-specific error structure and the need to introduce additional parameters associated with estimation of the unknown distribution of $\mu$, we restate several equations from Section 3. A subscript $k$ indicates the specific support point of the distribution of unobserved heterogeneity. Because the model is estimated for only one year, the year subscripts $a$ are dropped. Separating the unobserved heterogeneity components, the value functions in Equation 13 defining the utility of different insurance plans become

$$W^i(Z_0, \epsilon | \mu) = \nu_{0i} + \nu_1 V(Z_0 | d^i, \mu) + \eta_{1i} \mu_k + \epsilon^i \quad \forall i, \forall k.$$  \hspace{1cm} (16)

The per-period utility of an individual during the year is

$$U^h(X_t, d^h_t, \epsilon^h_t | d^i, \mu) = \alpha_{h0} + \frac{X_t^{\alpha_{h1}}}{\alpha_{h1}} + \alpha_{h2} d^h_{t1} + \alpha_{h3} d^{01} \cdot v_t + \alpha_{h4} \mathbf{H}_t$$

$$+ \sum_{j=0}^1 \left( \eta_{1(2+h)j, \mu_k} + \epsilon^i_t \right) d^h_{tj}, \quad \forall h, \forall j, \forall t.$$  \hspace{1cm} (17)
The unobserved individual random component can be interpreted as unobserved “healthiness” or attitudes toward care. As such, it is also likely to affect an individual’s probability of illness and the distribution of charges. The probability of illness in any period \( t \) is a function of the individual’s state as he enters period \( t \). The probability of illness in period \( t \) is

\[
\pi_t(Z_t|\mu) = \frac{\exp (\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 v_t + \gamma_3 H^*_t + \eta_4 \mu_k)}{1 + \exp (\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 v_t + \gamma_3 H^*_t + \eta_4 \mu_k)}.
\]  

(18)

The probabilities of treatment charges become

\[
\lambda_{h\ell} = \frac{\exp (\xi_{h\ell} + \xi_{h\ell} H_t + f(\xi, \ell) + \eta_5 \mu_k)}{1 + \sum_{\ell'=1}^{L} \exp (\xi_{h\ell'} + \xi_{h\ell'} H_t + f(\xi, \ell') + \eta_5 \mu_k)} , \quad \ell = 1, \ldots, L
\]

(19)

Finally, because the model is not solved for an individual’s lifetime, the value of future utility is parameterized as a function of the underlying state variables at the end of the year. The future value of lifetime utility is

\[
VF(Z_{T+1}|\mu) = \exp \delta_0 + \delta_1 Z_{T+1} + \delta_2 H_{T+1} Z_{T+1} + \eta_6 \mu_k.
\]

(20)

To summarize, limitations of the data prevent us from estimating the parameters of the optimization problem over multiple years as modeled. This requires that we make a few assumptions to “close” the model. We also introduce unobserved heterogeneity that can be decomposed into a permanent component that persists over time, \( \mu \), and a random shock, \( \epsilon \), that varies in all dimensions. We reduce dramatically the computational burden by imposing Bellman’s principle, by assuming the i.i.d. shocks enter additively and are Extreme value distributed, and by treating the value function at the end of the year as a loosely parametrized function of the end of year state variables.

### 5.2 The Likelihood Function

Solution of the optimization problem yields probabilities that define the likelihood of observing the behavior detailed in the data. The relevant probabilities are the probability of
choosing a particular insurance plan, the probabilities of illness, the probabilities of medical care utilization behavior during the year, and the probabilities of particular charges.

The backwards recursive solution of the optimization problem provides probabilities of choosing curative or preventive treatment alternative \( j \) in health state \( h \) and period \( t \), conditional on the insurance plan of an individual, the state vector at \( t \), and the random component of unobserved heterogeneity, of the form

\[
p(d_{t}^{hj} = 1 \mid d^t, \mathbf{Z}_t, \mu) = \frac{\exp \frac{\mathbf{V}^h_j(\mathbf{Z}_t|d^t, \mu)}{\rho}}{\sum_{j'=1}^{J} \exp \frac{\mathbf{V}^h_{j'}(\mathbf{Z}_t|d^t, \mu)}{\rho}} \quad \forall t, \forall h, \forall j .
\]  

(21)

The function \( \mathbf{V}(\cdot) \) is the deterministic part of the value of lifetime utility at period \( t \). The mean and variance of the Extreme Value distributed random component \( \epsilon \) are \( \xi + \rho \gamma \) and \( \frac{\pi^2 \rho^2}{6} \), respectively, where \( \gamma \) denotes Euler’s constant (\( \approx 0.5772 \)). Because differences in values of utility determine the optimal choice, the parameter \( \xi \) is assumed to be zero. The parameter \( \rho \) is normalized to one.

Once the problem has been solved back to period one, we can determine the choice probabilities of alternative insurance plans. The multinomial logit probabilities are

\[
p(d^i = 1 \mid \mathbf{Z}_0, \mu) = \frac{\exp \frac{\mathbf{W}^i(\mathbf{Z}_0|\mu)}{\rho}}{\sum_{i'=1}^{I} \exp \frac{\mathbf{W}^{i'}(\mathbf{Z}_0|\mu)}{\rho}} \quad \forall i .
\]  

(22)

We denote the probabilities of illness, conditional on the random unobserved component, as \( \pi_t(\cdot|\mu) \). Conditional probabilities of charge \( \ell \) are written \( \lambda_{h\ell}(\cdot|\mu) \). The parameters of the optimization problem are denoted \( \Theta \).

The likelihood contribution of individual \( n \), conditional on \( \mu \), is

\[
\mathcal{L}_n(\Theta|\mu) = \prod_{i=1}^{I} p(d^i = 1 \mid \mu) \prod_{t=1}^{T} \left( \prod_{t=1}^{T} \left( \prod_{j=1}^{J} p(d_t^{hj} = 1 \mid d^i, \mu)^{d_t^{hj}} \right) \prod_{j=1}^{J} p(d_t^{1j} = 1 \mid d^i, \mu)^{d_t^{1j}} \right)^{1(h_t=1)} \times 
\left( (1 - \pi_t(\cdot|\mu)) \prod_{j=1}^{J} p(d_t^{hj} = 1 \mid d^i, \mu)^{d_t^{hj}} \right)^{1(h_t=0)} .
\]  

(23)

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Unconditional on the unobserved heterogeneity, the likelihood contribution of individual \( n \) is
\[
L_n(\Theta, \theta) = \sum_{k=1}^{K} \theta_k \ L_n(\Theta|\mu_k),
\]
where \( \theta_k \) is the estimated weight associated with the estimated support point \( \mu_k \). The likelihood of observing the behavior of all individuals is
\[
L(\Theta, \theta) = \prod_{n=1}^{N} L_n(\Theta, \theta).
\]

Once we have estimated the parameters of the utility function, transition probabilities, and charge distributions, we can evaluate policy changes by simulating behavior under alternative health insurance characteristics.

6 Results, Policy Experiments, and Conclusions

In this paper, we have developed a dynamic stochastic structural model of an individual’s health insurance demand and medical care utilization and are in the process of estimating the model. This behavioral framework allows for predictions of the probabilities of curative and preventive treatment, of illness, of medical care charges, and of health insurance plan choice. A major contribution is that it explicitly accounts for the dynamic effects of changes in the effective price of medical care throughout the insurance year. This work also allows us to quantify the extent to which unobserved heterogeneity influences the health insurance choice as well as subsequent medical care utilization. Health economists have been unable to provide such a measure of adverse selection without imposing strict assumptions on the distribution of the unobservables.

I know you’d like to see results from estimation at this point, and hopefully you will at the seminar. More importantly, however, you’d like to see what happens to behavior when different insurance alternatives are introduced to the model. In my own decisionmaking
regarding whether to present a (near) completed paper with results versus work in progress, I guess I put more weight on useful constructive comments (that benefit me) than listener enlightenment (that benefits you)! :)

We have not completed estimation of a model for which we are satisfied. There are several extensions we plan to incorporate. These include expanding the health insurance choice set, reducing the length of a period, properly including purchases of prescription drugs, and adding seasonal dummies to capture variation in probabilities of illness over time. We also plan to include a second individual-specific factor that varies across time and captures time-specific shocks to the health state, the charge distribution, and utility.

Because we are estimating the structural parameters of an individual’s optimization problem regarding health insurance choice and medical care utilization, we are able to introduce alternative public policies and to predict the behavior of individuals under these new scenarios. Policy experiments include raising or lowering the deductible and observing behavioral changes in a set of simulated individuals. We can also introduce a monthly deductible amount, instead of an annual deductible, which may reduce the moral hazard of individuals by increasing the incidence of cost sharing. This policy is one that does not exist in the data and may produce behavior that resembles the behavior for which health insurance was intended. That is, people who are more severely ill and have the greatest need for care are protected against high costs; people who are less ill may think twice about seeking treatment if the out-of-pocket costs are high and there is no long term benefit to passing the deductible.

This model captures the dynamic behavior of individuals and provides an understanding of the effects of changes in the out-of-pocket price of health care over the insurance year. The behavioral model is useful for designing policies that are aimed at reducing the demand-side contribution to the upward-spiraling costs of health care.

Build it, and they will come. (Results that is!)
References


