Prescription Drugs, Medical Care, and Health Outcomes: A Model of Elderly Health Dynamics

by Zhou Yang, Donna B. Gilleskie, and Edward C. Norton

June 2006

Abstract

Health insurance specific to one type of medical care (e.g., prescription drug coverage) creates a change in medical care consumption behavior, beyond standard moral hazard, arising both from the differential cost-sharing and relative effectiveness of care in producing health. We model the choice of supplemental health insurance among Medicare beneficiaries, their medical care demand, and subsequent health outcomes using a dynamic model. Parameter estimates obtained with longitudinal individual-level data from the 1992-2001 MCBS allow us to simulate behavior under different drug coverage scenarios. Prescription drug coverage increases drug expenditures by 20% to 35% over a five-year period. While mortality rates fall slightly, the survivors have poorer health, leading to higher total medical expenditures.

This research is funded by the National Institute on Aging Grant Number R01-AG16600. We appreciate comments from David Blau, Richard Hirth, Xin Li, Betsy Sleath, Sally Stearns, Morris Weinberger, and seminar and conference participants at the University of North Carolina at Chapel Hill, Michigan State University, the University of Wisconsin, the 4th World Congress of the international Health Economics Association, and the 15th Annual Health Economics Conference. We also acknowledge Tom Mroz for providing the discrete factor random effect subroutine that we adapted for estimation of our model. Comments are welcome at `zyang@email.unc.edu`, `donna_gilleskie@unc.edu`, or `edward_norton@unc.edu`.

1 Introduction

One of the fundamental questions in health economics is how health insurance affects the demand for medical care. A related question concerns the relative effectiveness of various medical care inputs in producing health. Although general health insurance causes moral hazard (i.e., an increase in the demand for medical care as a result of the decreased net price of care),[1] health insurance that is specific to just one type of medical care — prescription drugs, long-term care, or mental health care — could influence consumption of other types of care. This change in medical care consumption behavior stems both from the differential cost-sharing features of insurance for different types of care as well as the relative effectiveness of each type of care in producing or maintaining health. The behavioral effect, however, could lead to more efficient use of medical care resources if increased demand for a newly-covered service reduces costly expenditures of other types of care and if the associated changes in care improve health over time. Alternatively, changes in behavior associated with additional coverage in one area may cause unnecessary costs if consumption of costly or redundant care escalates or if health outcomes deteriorate.

We contribute to the understanding of this behavior by modeling how health insurance affects medical care expenditures and health outcomes in a dynamic framework. Health insurance for one type of care lowers the price of that type of care and thus increases the quantity of care received. It may also alter the quantity of other types of care demanded. In addition to the price-driven changes in consumption behavior, the relative differences in the marginal effectiveness of different types of care in producing health lead to different input allocations. The resulting changes in morbidity and mortality affect all future medical care expenditures. This process implies that an empirical study investigating the effects of drug coverage on medical care expenditures must account for all types of medical care consumption. Furthermore, it must examine medical care expenditures over time because they both influence and depend on changes in morbidity and mortality. Finally, it must incorporate observable and unobservable individual differences that influence behavior.

[1] This form of *ex post* moral hazard is typically used to describe the behavior of a person after he becomes sick. *Ex ante* moral hazard refers to disincentives induced by health insurance for an individual to reduce his probability of falling ill.

The recent expansion of Medicare from hospital and physician services coverage for the elderly (Parts A and B) to one that includes optional coverage of prescription drugs (Part D) will provide an interesting social experiment for evaluating the effect of one type of insurance on consumption of other types of medical care and, perhaps more importantly, on the health of the elderly. Unfortunately, we must wait a few years; careful examination of what are obviously dynamic outcomes can occur only at some point in the future.[2] However, existing sources of prescription drug coverage, and health insurance in general, provide some insight into the relationship between the demands for medical care services of all types and the subsequent production of health. To examine these relationships we use panel data on elderly Medicare-covered individuals to estimate a dynamic model of supplemental insurance selection (which may or may not include prescription drug coverage); demand for hospital services, physician services, and prescription drugs; health shocks; and health production.

Our model can be used to understand how prescription drug coverage, such as Medicare's new Part D, affects total medical care expenditures and health over time. One argument in favor of the Medicare expansion is the expected reduction in other health care expenditures. Support for this argument cannot be tested within a static framework, as others have tried to do. Projections of long-run costs associated with drug coverage should reflect not only the immediate moral hazard effect but also the longer-run changes in morbidity and mortality associated with changes in both drug use and other medical care use over time (substitutes or complements). Increased prescription drug use may improve Medicare beneficiaries' general health, reduce the onset of chronic illness and/or its complications, or decrease mortality leading to opposing forces. Improved health and lower disability rates may reduce inpatient and outpatient expenditures in the short run. However, decreased mortality may increase the number of Medicare beneficiaries and the total demand for Medicare-covered services in the long run. Modeling the health and behavior of marginal survivors, those individuals who would have died without prescription drug coverage but who live longer with it, is critical to understanding the full costs and benefits of prescription drug coverage.

[2]In December 2003, the president of the U.S. signed into law the Medicare Prescription Drug Improvement and Modernization Act in the greatest expansion of Medicare benefits since its creation in 1965. The first beneficiaries began receiving drug coverage in January 2006.

Our dynamic behavioral analysis allows the increase in prescription drug use induced by drug coverage to affect subsequent total health care expenditures of the elderly through changes in health status over time. We use data from the longitudinal Medicare Current Beneficiary Survey Data (MCBS) from 1992 to 2001 to jointly estimate a system of empirical equations representing supplemental insurance coverage choices, dynamic drug and other medical care demand, and health production. Specifically, our findings quantify the effect of drug coverage (through Medicaid, employer and private insurance plans, or Medicare's managed care option (Part C)) on the demand for drugs as well as Medicare Part A (hospitalization) and Part B (physician) services among Medicare beneficiaries, the effect of each medical care input on functional status and mortality, and the effect of health on subsequent medical care consumption over time. We evaluate the long-run (5-year) effect of drug coverage by simulating behavioral outcomes under different drug coverage scenarios, and updating endogenous explanatory variables, year by year. Universal prescription drug coverage would increase prescription drug expenditures in our sample by 20 to 35% (depending on the type of drug coverage provided) over five years. The associated changes in inpatient care and physician services differ depending of the source of drug coverage. While some of the increase is directly attributable to changes in insurance, the increase in total expenditures results from changes in health also. Long-run survival probabilities increase, leading to larger proportions of elderly survivors with functional limitations. Our projections of changes in both expenditures and health, however, are smaller than those produced by extrapolating static models that fail to incorporate the dynamic consequences of increased prescription drug use on health and other Medicare-covered services.

This paper extends the literature on moral hazard induced by health insurance, addresses the adverse selection inherent in insurance decisions, evaluates the role of different medical care inputs in health production, and fills a void in the policy debate about the Medicare prescription drug benefit. In Section 2 we discuss the relevant literature and our contributions. Dynamic behavioral models are appropriate when studying complex behavior over time where changes in the composition of individual characteristics are associated with the behavior of interest. Details of both the theoretical motivation and our empirical specification are provided in Section 3. Our longitudinal data, described in Section 4, are sufficiently rich in both health and expenditure information to estimate the dynamic empirical model. In Section 5 we discuss the use of our estimated model to evaluate the long-term effects of drug coverage, not only for the sample as a whole, but also for several interesting subpopulations defined by specific health conditions. Section 6 summarizes our findings.

2 Background and Literature Review

Even without Medicare prescription drug coverage, elderly Americans (age 65 and older) spend a large amount on outpatient prescription drugs. In 1995, approximately 85 percent of the noninstitutionalized elderly had at least one prescription, and the average annual outpatient prescription drug expenditure was around $600 per person and $22 billion in total (Poisal et al., 1999). Although the elderly only account for one-eighth of the total population, their drug expenditures account for one-third of all drug expenditures in the U.S. (DHHS, 1998; Long, 1994). Elderly persons have greater demand for prescription drugs because of worse general health, higher disability rates, and a higher prevalence of chronic diseases (Adams et al., 2001a; Blustein, 2000; Johnson et al., 1997; Lillard et al., 1999; Poisal et al., 1999; Rogowski et al., 1997; Soumerai and Ross-Degnan, 1999; Stuart and Coulson, 1994).

Despite the high demand, insurance coverage of outpatient prescription drugs is limited among the elderly. Before 2006, the Medicare program did not cover most outpatient prescription drugs. However, about 65% of Medicare beneficiaries have some drug coverage from at least one supplemental insurance plan, leaving 35% who must cover the full cost of outpatient prescription drugs out of pocket. Among those with drug coverage (which may be from multiple sources), about 44% have employer-provided health insurance (either as retirees or active workers), 16% hold privately-purchased individual coverage, 16% have Medigap insurance, 11% are covered through a Medicare HMO, 17% are on Medicaid, and 4% have other publicly-provided coverage, including Veteran Assistance or state Pharmacy Assistance (Poisal et al., 1999). Adverse selection suggests, however, that those who purchase additional insurance beyond Medicare are those who expect to have higher than average expenditures.

Although more than half of the Medicare beneficiaries have at least one type of drug coverage, none of these drug insurance plans are comprehensive. Out-of-pocket payment is still the largest source of outpatient drug payment for the elderly, and accounts for 50% of total drug expenditures (Poisel et al., 1999). Several studies show that lack of sufficient insurance coverage is one major reason for under-use of prescription drugs. Steinman and colleagues (2001) found that, among elderly people age 70 and older in the U.S., chronically-ill patients without drug insurance were more likely to skip doses or avoid using medication than those with drug insurance. Federman and colleagues (2001) found that, among Medicare beneficiaries with coronary heart disease, those without drug insurance have lower use of statins, which is a class of expensive and effective cardiovascular drugs, compared with those who have prescription drug insurance. Poisal and Murray (2001) found that elderly Medicare beneficiaries with drug coverage received 9% more prescriptions on average from 1997 to 1998, while those without any drug coverage received 2.4% fewer prescriptions from one year to the next. Their findings suggest that moral hazard may be an issue among the insured, but that lack of drug insurance (and hence high out-of-pocket costs) may also distort consumption over time. Even among those Medicare beneficiaries who have drug insurance, high copayment rates or other cost-sharing limitations may restrict the appropriate use of clinically-essential drugs (Reeder and Nelson, 1985; Soumerai et al., 1987; Soumerai and Ross-Degnan, 1990; Soumerai et al., 1991; Soumerai et al., 1994).

Most studies of the potential costs of a Medicare prescription drug benefit are cross-sectional and provide only a point-in-time correlation between drug coverage and drug utilization. These studies suggest that insurance increases prescription drug use, and the more generous plans have the strongest positive effects (Adams et al., 2001b; Blustein, 2000; Lillard et al., 1999; Long, 1994; Poisal et al., 1999; Rogowski et al., 1997). Other cross-sectional studies conducted at the state or community level draw similar conclusions (Fillenbaum et al., 1993; Stuart and Coulson, 1993; Stuart and Grana, 1995).

To better understand the effects of increased drug coverage among the elderly, it is necessary to consider both the effect of insurance on drug use, as well as the effect of drug use on other health care costs and health outcomes. With regard to the effect of drug use on non-drug medical care expenditures, Soumerai and colleagues (1991) found that a reduction in use of outpatient drugs due to a prescription cap in New Hampshire led to increased hospital and nursing home admission rates among elderly beneficiaries over one year. For mentally-ill patients, the increase in the cost of non-drug medical services even exceeded the savings in reduced prescription drug use (Soumerai et al., 1994). A study conducted in Canada revealed that greater consumer cost-sharing for prescription drugs led to a reduction in consumption of essential drugs, and higher rates of adverse health events and emergency room visits among elderly persons (Tamblyn et al., 2001). These studies, however, do not consider explicitly the effect of altered drug use on patient mortality or morbidity.

Turning to the effect of drug use on health outcomes, Gowrisankaran and Town (2004) analyzed county-level mortality rates over time and found that greater enrollment in Medicare managed care insurance plans without a drug benefit was associated with higher mortality but found no association between mortality and Medicare managed care plans with drug coverage. Federman et al. (2001) and Lichtenberg (2003) found that greater use of clinically-essential drugs or newer drugs may decrease the population mortality rate. None of these studies, however, investigate morbidity and functional status among the survivors and their subsequent medical care expenditures. Some researchers argue that chronic diseases are the main reason for functional disability and therefore suggest that the development and use of new drugs could decrease disability rates (Cutler, 2001; Ferrucci and Guralnik, 1997).

Measurement of the effect of drug use on health outcomes (both mortality and morbidity) over time is necessary for predicting the net cost of a Medicare drug benefit. For example, studies that fail to consider the possible reduction in disability rates due to drug use may overstate the net cost of the drug benefit given the positive correlation between disability and inpatient care expenditures among the elderly (Stearns et al., 2006). If the elderly live longer but healthier lives, then the total medical care cost at the population level may not necessarily increase. Alternatively, studies that fail to consider how drug use affects morbidity and mortality may understate the long-term net costs of a Medicare drug benefit. A lower mortality rate and greater longevity will increase the number of Medicare beneficiaries and lead to greater demand for all Medicare-covered health care services. Additionally, the distribution of health among survivors changes: increased survival may imply a larger proportion of disabled elderly. The lack of longitudinal analyses of individual behavior that could explain the complicated causal relationship between drug utilization, changes in health status, and subsequent expenditures on other medical care services among the elderly population is a striking omission from the existing literature (Adams et al., 2001a). This paper seeks to fill the void.

3 Model of Elderly Health Dynamics

3.1 Theoretical Motivation

Economic theory provides a framework for analyzing medical care demand and health production over time. The seminal work of Grossman (1972) adopted the household production approach to model a consumer's lifetime demand for health, and derived demand for medical care, where health exhibits both consumption value and investment value. Individuals receive utility each period from the services of a health stock (i.e., healthy days). Health inputs (medical care and time spent in health producing-activities) augment the natural depreciation of the health stock over time.

In the thirty-five years since Grossman's formalization of health behavior, he and other health economists have extended his model to incorporate uncertainty, health insurance, preventive care, and retirement policies, among other things. However, few economists have attempted to parameterize and estimate the optimization behavior of individuals with regard to their health and health care consumption. Keeler, et al. (1977) suggested that the dynamic behavior be characterized by Bellman equations and the uncertainty made explicit. Yet, only a handful of empirical research of this sort has materialized; only four papers to our knowledge (Gilleskie, 1998; Crawford and Shum, 2005; Davis and Foster, 2005; and Khwaja, 2001) explain medical care and non-medical input decisions and their influence on health outcomes in a manner suggested in health economics' infancy by Grossman and reiterated by Keeler and his colleagues. That is, rather than simply measuring correlations or stand-alone production functions, these authors estimate the preferences, constraints, and expectations of forward-looking individuals that allow for evaluation of interesting health policy alternatives.[3]

Much of the empirical work on medical care demand has been based on reduced form models, or has exploited changes or differences in policies to provide "natural" exogenous variation in the determinants of demand. This outcome arises largely because of the difficulty of solving, and estimating structural parameters of, optimization problems that involve many decisions, numerous alternatives, and large state spaces. Various authors in the body of empirical work have tried to address issues of uncertainty, unobserved heterogeneity, and dynamics, but a unifying framework that captures each of these issues remains elusive. However, estimable approximations representing the structural demand equations, health production functions, and uncertain health shocks can be derived from a theoretical framework that captures the dynamic utility maximization problem under uncertainty. We provide such a framework below.

Our general theoretical model introduces the variables used in the empirical specifications in Section 3.2. For brevity, we reduce the dimension of some variables in the theoretical discussion. Following Grossman, utility is a function of health, but we also allow medical inputs to directly influence current period utility. Additionally, we allow for the possibility that medical care utilization in the previous period may alter current period utility of medical care directly rather than only indirectly through its influence on health transitions from period to period. Health stock transitions are uncertain, but the technology is assumed to be known. We also allow health shocks to randomly influence per-period consumption and subsequent health stock transitions. Analogous to our empirical specification, we model the demand for hospital services, physician services, and prescription drugs.

A Bellman equation captures the dynamic and uncertain lifetime value of medical care consumption alternatives this period conditional on health insurance coverage and information known up to the current period. The lifetime value of hospital services, physician

[3]Gilleskie (1998) models daily medical care and absence decisions over an episode of acute infectious, parasitic, or respiratory illness. Crawford and Shum (2005) model prescription drug decisions during an episode of gastro-intestinal illness. Davis and Foster (2005) model semi-annual mental health care decisions during childhood. Khwaja (2001) models annual smoking, exercise, drinking, and medical care decisions over an adult lifetime.

services, and prescription drugs alternatives ($A_t = a, B_t = b$, and $D_t = d$) in period t is comprised of current period expected utility plus a random alternative- and health shock- specific error and the expected present discounted value of utility in the future. More specifically,

$$\begin{aligned}
V_{abd}(A_{t-1},B_{t-1},D_{t-1},H_t,C_t,X_t,Z_t,\epsilon_t|I_t) \quad = \\
\sum_{s=0}^{1}\Big[p(S_t = s \,|H_t,C_t,X_t)U(C_t,A_t=a,B_t=b,D_t=d,H_t,S_t=s,A_{t-1},B_{t-1},D_{t-1},X_t) + \epsilon_{st}^{abd}\Big] \qquad (1) \\
+\beta\sum_{h=0}^{H}[p(H_{t+1} = h|H_t,C_t,S_t=s,A_t=a,B_t=b,D_t=d,X_t)W(X_{t+1},Z_{t+1}|H_{t+1}=h,C_{t+1})] \\
\forall a, b, \text{ and } d, \quad \forall t = 1, \ldots, T.
\end{aligned}$$

The arguments of the alternative-specific value function, $V_{abd}(\cdot)$, represent the information known to the individual at the beginning of the period and include lagged medical care utilization, health entering the period (H_t), presence of chronic conditions (C_t), exogenous individual characteristics (X_t), exogenous prices (Z_t), and all current and lagged values of the unobserved (by the researcher) components of utility. The value of each alternative also depends on the insurance coverage (I_t) selected by the individual prior to health shocks and utilization decisions in period t. Composite consumption of other goods (G_t) is defined by the budget constraint. That is,

$$G_t = Y_t(p_t^i) - p_t^a(I_t)\cdot A_t - p_t^b(I_t)\cdot B_t - p_t^d(I_t)\cdot D_t \qquad (2)$$

where $Y_t(\cdot)$ represents per-period income net of the insurance premium for plan i, and the price of the composite consumption good is normalized to one. Prices of medical care, the insurance premium, and insurance cost-sharing and non-price characteristics are components of the exogenous price vector $Z_t = (p_t^a, p_t^b, p_t^d, p_t^i, n_t^i)$. Out-of-pocket prices of care are determined by the cost-sharing features of the health insurance plan. Savings is not modeled, for simplicity.

The model captures the uncertainty of both per-period health shocks and the stochastic nature of health stock transitions. In this model, whether one has ever had a chronic condition entering period t, C_t, is updated each period based on the observance of health shocks, S_{t-1}, in the previous period. The uncertain last period of decisionmaking, $t = T$, is followed by death (i.e., $H_{T+1} = H$) where increasing values of $h = 0, \ldots, H$ represent decreasing values of the health stock.

Future utility in Equation (1) is captured by the maximal value of lifetime utility at period $t+1$ *unconditional* on the future insurance selection, $W(\cdot)$, where

$$W(X_{t+1}, Z_{t+1}|H_{t+1}, C_{t+1}) = \mathrm{E}_t \left[\max_{i'} W_{i'}(X_{t+1}, Z_{t+1}, \epsilon^{i'}_{t+1}|H_{t+1}, C_{t+1})\right], \forall t. \tag{3}$$

The value of each insurance alternative, i, depends on the non-price attributes of the plan and expected health care utilization in the future given cost-sharing characteristics associated with the plan. That is,

$$\begin{aligned} W_i(X_{t+1}, Z_{t+1}, \epsilon^{i}_{t+1}|H_{t+1}, C_{t+1}) \quad &= \\ f\big(X_{t+1}, Z_{t+1}, H_{t+1}, C_{t+1}, V(A_t, B_t, D_t, H_{t+1}, C_{t+1}, X_{t+1}, Z_{t+1}|I_{t+1}=i)\big) &+ \epsilon^{i}_{t+1} \ \forall i, \forall t. \end{aligned} \tag{4}$$

where the maximal value of lifetime utility *conditional* on insurance (i.e., the last argument of $f(\cdot)$ in Equation (4)) is

$$\begin{aligned} V\big(A_t, B_t, D_t, H_{t+1}, C_{t+1}, X_{t+1}, Z_{t+1}|I_{t+1}\big) \quad &= \\ \mathrm{E}_t \left[\max_{a'b'd'} V_{a'b'd'}\big(A_t, B_t, D_t, H_{t+1}, C_{t+1}, X_{t+1}, Z_{t+1}, \epsilon_{t+1}|I_{t+1}\big)\right], \forall t \end{aligned} \tag{5}$$

and the expectation at time t is taken over the uncertain values of alternative specific error terms, ϵ_{t+1}, next period. Solution to the optimization problem yields medical care and insurance demand equations, a health stock production function, and the probability of a health shock. These structural equations derived from the model above are presented in our empirical specification below.

3.2 Empirical Specification

Our empirical model has five key features: 1) observed supplemental prescription drug coverage decisions depend on unobserved individual characteristics that also influence the demand for prescription drugs (endogenous insurance coverage); 2) current consumption of different types of medical care may be correlated (joint estimation of medical care demand equations); 3) medical care demand and insurance decisions are determined by both the stock and the flow of health (joint estimation of general health and health shocks); 4) current medical care consumption influences future health which, in turn, determines future consumption (joint estimation of endogenous medical care inputs and health outcomes); and 5) past medical care consumption influences current consumption partially through pathways other than health (direct effects of lagged behavior).

We begin by specifying equations for supplemental insurance coverage, health shocks, dynamic medical care demand, and health outcomes over time. Generally, these equations are functions of theoretically-relevant variables described as observable and unobservable heterogeneity. The observed heterogeneity in our set of equations includes the endogenous time-varying variables: supplemental insurance coverage (I_t and J_t); health stock and health shocks (H_t, C_t, and S_t); and medical care consumption (A_t, B_t, and D_t). Exogenous time-varying county-level variables likely to influence health, the supply or price of insurance, and the supply or price of medical care (Z_t^H, Z_t^I, and Z_t^P) also enter relevant equations. Additionally, observed outcomes are influenced by exogenous permanent and time-varying economic and demographic information (X_t).[4] The timing and use of lagged or contemporaneous variables in specific equations are described below.

This observed variation explains only part of the variation in outcomes of interest in the data. Unobserved individual characteristics likely influence many or all of the behaviors we model. To allow for this correlation, we estimate the set of insurance, medical care demand, and health equations jointly rather than separately. Our empirical framework incorporates two specific types of unobserved heterogeneity. One type is permanent individual heterogeneity, such as unobserved attitudes toward medical treatment or quality of health care providers. For example, a patient who prefers outpatient care to inpatient care is more likely to seek drug treatment than a patient who better tolerates inpatient care. Similarly, he may choose supplemental insurance with better prescription drug coverage.

The other type of unobserved heterogeneity is time-varying individual heterogeneity. The time unit of analysis in this study is a calendar year. Within this time interval the health status of Medicare beneficiaries may change significantly. Although observed health shocks and medical care inputs help explain health transitions over a year (i.e., health production), unobserved factors also influence changes in health status. An example of an unobserved characteristic that may vary over time for a particular individual is the unobserved rate of natural deterioration of her health. Although medical care consumption may help people

[4]Refer to Tables 3 and 4 for specific variable names and descriptions.

maintain good health, the health status of elderly people deteriorates naturally because of aging and, more importantly, at different rates for different people. Another example is an unobserved health shock in any particular year.

Let u_t^e represent the unobserved error term associated with a particular equation e (in our set of jointly estimated equations) at time t. To define the unobserved individual heterogeneity, we decompose the error term of each equation into three components. The first part, μ, captures permanent, or time-independent, unobserved individual heterogeneity; the second part, ν_t, represents time-varying unobserved individual heterogeneity; and the third part, ε_t^e, is a serially uncorrelated error term for equation e. Let ρ^e be the factor loading on μ and ω^e be the factor loading on ν_t for equation e. The error decomposition is

$$u_t^e = \rho^e \mu + \omega^e \nu_t + \varepsilon_t^e \tag{6}$$

where vectors ρ^e, μ, ω^e, and ν_t are estimated parameters of the empirical model.[5] The *i.i.d.* error is assumed to be normally distributed, $\varepsilon_t^e \sim N(0, \sigma_e^2)$, for OLS equations with continuous outcomes and the standard error, σ_e, is jointly estimated with the other parameters. The errors in dichotmous and polychotomous outcome equations with logit or multinomial logit specifications have an extreme value distribution. The set of jointly estimated equations (insurance, medical care demand, and health outcomes) and specification of their observed and unobserved components is provided next.

We assume that all elderly persons (age 65 and older) are covered by Medicare (and virtually all elect both Part A and Part B Medicare coverage in our data). Supplementation of Medicare coverage, however, is a choice. Each period, an elderly person decides whether to supplement her Medicare coverage where $I_t = 0$ indicates no additional coverage, $I_t = 1$ is Medicaid coverage, $I_t = 2$ is private coverage (Medigap), and $I_t = 3$ is the Medicare HMO option. Assuming an Extreme Value distribution of the additive error term in the alternative-specific value function for insurance defined in Equation (4), the decision rule is

$$\Pr(I_t = i) \;=\; \Pr\left(W_i(X_t, Z_t, \epsilon_t^i | H_t, C_t) \geq \max[W_{i'}(X_t, Z_t, \epsilon_t^{i'} | H_t, C_t), \forall i' \neq i]\right)$$

[5]The discrete mass points of the permanent and time-varying heterogeneity distributions are denoted $\mu = (\mu_m, m = 1, \ldots, M)$ and $\nu_t = (\nu_{\ell t}, \ell = 1, \ldots, L)$, respectively, where M and L are the number of mass points in the discrete approximations to the distributions. The factor loadings measure the weight on the heterogeneity component for each outcome, o, of each equation, e, where $\rho^e = (\rho_o^e, o = 1, \ldots, O)$ and $\omega^e = (\omega_o^e, o = 1, \ldots, O)$ for each equation with more than two outcomes. Appropriate normalizations are imposed for identification.

$$= \Pr(\epsilon_t^i \geq \max[W_{i'}(X_t,Z_t,\epsilon_t^{i'}|H_t,C_t),\forall i'\neq i] - \overline{W}_i(X_t,Z_t|H_t,C_t))$$

$$= \frac{\exp\frac{\overline{W}_i(X_t,Z_t|H_t,C_t)}{\kappa}}{\sum_{i=0}^{3}\exp\frac{\overline{W}_i(X_t,Z_t|H_t,C_t)}{\kappa}} \quad \forall i$$

where $\overline{W}_i(\cdot)$ indicates the deterministic part of the insurance-specific value function and κ defines the mean and variance of the Extreme Value error. As an alternative to solving the optimization problem specified in the previous section and estimating the primitive parameters of the model, we approximate the polydichotomous supplemental insurance probabilities as a function of the theoretically-relevant variables known by the individual at the beginning of the period. Written in log odds form, these choice probabilities are specified as

$$\begin{aligned} \ln\left[\frac{\Pr(I_t=i)}{\Pr(I_t=0)}\right] &= \eta_{i0} + \eta_{i1}X_t + \eta_{i2}H_t + \eta_{i3}C_t \\ &\quad +\eta_{i4}Z_t^I + \eta_{i5}t + \rho_i^I\mu + \omega_i^I\nu_t, \\ &\quad i = 1, 2, \text{ and } 3. \end{aligned} \tag{7}$$

An individual selecting either a private supplemental plan or the Medicare HMO option may or may not have prescription drug coverage. An indicator of drug benefits ($J_t = 1$) is modeled as a logit outcome where

$$\begin{aligned} \ln\left[\frac{\Pr(J_t=1|I_t=2\text{ or }3)}{\Pr(J_t=0|I_t=2\text{ or }3)}\right] &= \xi_0 + \xi_1X_t + \xi_2H_t + \xi_3C_t + \xi_4\mathbf{1}(I_t=3) \\ &\quad +\xi_5Z_t^I + \xi_6t + \rho^J\mu + \omega^J\nu_t \ . \end{aligned} \tag{8}$$

These insurance decisions, assumed to occur at the beginning of a year t, are a function of observed health entering the period (H_t and C_t), as well as an exogenous measure of per county HMO penetration each year (Z_t^I), which serves to capture both availability and price of insurance. Time trends are included to control for general variation in coverage that occurs over time.[6] We allow the observed supplemental health insurance and drug coverage of an individual to be influenced by unobservable individual characteristics (e.g., health history or preferences for care), μ and ν_t, that are likely to also influence medical care decisions and health transitions. Assumed exogeneity of health insurance and drug coverage decisions would bias estimates of its effect on drug consumption if such adverse selection

[6]Participation in the Medicare managed care plans (Part C) increased throughout the 1990s (from about 2.5 million enrollees in 100 plans) and hit its peak in 1999 (of over 6 million enrollees and 350 plans). Participation has steadied and decreased slightly throughout the early 2000s.

occurs. Correct estimates of the effects of insurance are crucial for evaluating the costs and benefits of prescription drug coverage.

Theory suggests that demand for medical care during the year is influenced by one's stock of health (H_t) and existing chronic conditions (C_t). In each year, functional status serves as our measure of health stock (H_t) at the beginning of the annual observation period t and is defined by ADL and IADL limitations.[7] We model the existence in year t of four major chronic health concerns of the elderly ($C_t = (C_t^1, C_t^2, C_t^3, C_t^4)$): $1 \equiv$ heart problems (including high blood pressure, stroke, and heart disease); $2 \equiv$ respiratory problems (such as bronchitis and emphysema); $3 \equiv$ cancer; and $4 \equiv$ diabetes. But medical care consumption is also dictated by health shocks (S_t) or adverse events that occur during the year. These shocks are likely correlated with permanent and time-varying unobservables that determine other health-related behaviors such as insurance selection, medical care demand, and health transitions. As such, our equation system includes the probability of health shocks of type k where k indicates health shocks of the types enumerated above. That is,

$$\begin{aligned} \ln\left[\frac{\Pr(S_t^k = 1)}{\Pr(S_t^k = 0)}\right] &= \phi_0^k + \phi_1^k X_t + \phi_2^k H_t + \phi_3^k C_t \\ &\quad + \phi_4^k Z_t^H + \rho^{Sk}\mu + \omega^{Sk}\nu_t, \\ &\quad k = 1, 2, \text{ or } 3. \end{aligned} \tag{9}$$

Note that individuals with or without the existence of chronic condition k entering year t may experience a health shock of type k in year t. An adverse health shock among individuals free of disease (i.e., $C_t^k = 0$ and $S_t^k = 1$) implies that they have the chronic condition ($C_{t+1}^k = 1$) in the subsequent period. We also assume that these conditions are never cured (i.e., if $C_t^k = 1$, then $C_{t+1}^k = 1$).[8] Health shocks are a function of demographic characteristics (X_t), health

[7] We estimated the model using the broader, but more subjective, measure of self-reported health status and found very few differences in the results.

[8] As such, C_t is a stochastic variable defined by the onset of a health shock of a particular type. It is endogenous since individuals have the ability to influence their health stock (H_t) which affects the probability of a health shock. While we model the existence of diabetes as an initially observed chronic condition, we do not model the probability of a diabetes health shock for three reasons. First, the onset of diabetes (after the first period of observation) among our older sample is very small (although existence is near 20%). Second, the health shocks that diabetics incur typically include cardiovascular, cerebrovascular, and respiratory problems, which we do model. Third, the MCBS allows for up to three ICD-9 (International Classification of Diseases, 9th Edition) codes for classification of medical claims. For most health shocks of diabetics, a diabetes code is not listed among the three.

and existence of chronic conditions entering the current period (H_t and C_t), and exogenous differences in health-related variables across counties (Z_t^H), such as measures of air quality.

Our next set of equations describes demand for medical care.[9] The distribution of medical expenditures is highly skewed, with some people having zero expenditures. Following much of the literature in health economics, we model expenditures in year t using a logit equation to estimate utilization (or the probability of any expenditures) and the natural log of expenditures, if any, as a continuous outcome. Letting q indicate either Part A, Part B, or prescription drug expenditures, the probability of any such expenditures follows a logit specification of the form

$$\begin{aligned}
\ln\left[\frac{\Pr(q_t>0)}{\Pr(q_t=0)}\right] &= \alpha_0^q+\alpha_1^qX_t+\alpha_2^qH_t+\alpha_3^qC_t+\alpha_4^qS_t \qquad (10)\\
&+\alpha_5^q\mathbf{1}(A_{t-1}>0)+\alpha_6^q\mathbf{1}(B_{t-1}>0)+\alpha_7^q\mathbf{1}(D_{t-1}>0)\\
&+\alpha_8^qI_tJ_t+\alpha_9^qZ_t^P+\alpha_{10}^qt+\rho^{q1}\mu+\omega^{q1}\nu_t,\\
&q=A,B,\ \text{or}\ D.
\end{aligned}$$

Log expenditures on q, if any, are modeled as

$$\begin{aligned}
\ln(q_t|q_t>0) &= \delta_0^q+\delta_1^qX_t+\delta_2^qH_t+\delta_3^qC_t+\delta_4^qS_t \qquad (11)\\
&+\delta_5^q\mathbf{1}(A_{t-1}>0)+\delta_6^q\mathbf{1}(B_{t-1}>0)+\delta_7^q\mathbf{1}(D_{t-1}>0)\\
&+\delta_8^qI_tJ_t+\delta_9^qZ_t^P+\delta_{10}^qt+\rho^{q2}\mu+\omega^{q2}\nu_t,\\
&q=A,B,\ \text{or}\ D.
\end{aligned}$$

The two-equation specification of demand allows variables of interest to have a different marginal effect on the probability of any expenditures and the level of expenditures.[10] Explanatory variables include demographic and economic characteristics such as income and

[9]Specification of the utility function parameters, $U(\cdot)$, and the structural parameters of the insurance function, $f(\cdot)$, would yield estimates of the policy-invariant primitives of the individual's optimization problem. Our approximations, using Taylor-series expansions of the arguments of $\overline{V}_{abd}(A_{t-1},B_{t-1},D_{t-1},H_t,C_t,X_t,Z_t|I_t)$ and $\overline{W}_i(X_{t+1},Z_{t+1}|H_{t+1},C_{t+1})$, provide estimable structural medical care and insurance demand equations. Replacement of right-hand side endogenous variables with their exogenous components would produce reduced-form equations, but we do not estimate those. Rather, since we model behavior over time and have data on individuals over time, unbiased estimates of the endogenous arguments of demand are recoverable with appropriate econometric techniques.

[10]In our data, about 79%, 16% and 10% of the person observations have zero expenditures on hospital care, physician services, and prescription drugs, respectively.

education (X_t), health stock (H_t and C_t), and health shocks (S_t).[11] The interaction of I_t and J_t represents the five supplemental insurance alternatives (relative to no supplemental coverage) which are Medicaid, private (with and without prescription drug coverage) and Medicare managed care (with and without prescription drug coverage).

Theory suggests that demand for a particular type of medical care is a function of its own price, as well as the price of substitutes and compliments. Price is, in part, captured by insurance. We also control for average Medicare reimbursement rates for hospital and physician services by county and year (Z_t^P). Other supply-side variables such as the number of hospitals, hospital beds, and physicians per 1000 population by county and year are included in Z_t^P. HMO penetration (Z_t^I) captures the effect of HMO presence on insurance choices, but this measure also enters the demand equations to reflect lower (negotiated) prices of services in areas of high HMO concentration.[12]

Because this study seeks a comprehensive understanding of how drug coverage affects prescription drug use and subsequent health outcomes, we cannot ignore the correlated use of other medical services such as hospital and physician care. Prescription drug use may be a complement to or a substitute for these other types of medical care. That is, a hospital stay may require physician care follow-ups and prescription pain relief exhibiting positive contemporaneous correlation in (annual) use. Alternatively, prescription drug use may prevent, delay, or substitute for costly hospitalization reflecting negative contemporaneous correlation. Thus, the demands for each type of medical care are correlated through both permanent individual unobservables (μ) and contemporaneous time-varying individual unobservables (ν_t).

Some theories of demand suggest that the current utility of consumption of addictive goods may depend on the use of that good in previous periods (Becker and Murphy, 1988 and Becker, et al., 1994). While we are not suggesting that consumption of medical care is

[11] We allow particular health shocks in period t to influence annual medical care expenditures. The influence of chronic conditions that do not result in current period claims (or shocks) occurs indirectly through transitions in the health stock as well as through health shocks that affected utilization in the last period. It also enters directly indicating that a chronic condition may alter medical care consumption behavior even if a health shock does not occur.

[12] Cost-sharing characteristics of insurance plans, such as co-payments, deductibles, or coinsurance rates, are not available in the MCBS data. These data do report out-of-pocket costs, as well as claims, but particular plan details are not reported.

addictive, utilization of particular types of care may be habitual or the effectiveness may be dependent on continued use. For example, some Medicare beneficiaries develop stable and trustworthy relationships with their outpatient care providers over time. An individual with more physician contact (or a regular source of care), all else equal, may be more likely to fill prescriptions and use other forms of medical care in the future because of the relationship that has been established between patient and provider. Similarly, hospitalization in the previous period, for example, may require follow-up physician care or prescription medication. For this reason we include lagged indicators of previous use of each type of medial care in current demand equations.[13]

Time trends are also included in the utilization and expenditures equations to capture additional time-series variation in particular types of care. In particular, consumption of prescription drugs has increased considerably over the 1990s. Much of this increase may be related to health or insurance coverage, but a significant amount may be due to exogenous changes in advertising and production of new drugs. Additionally, we show that it is important to appropriately model serial correlation in individual unobservables that might lead to an apparent statistical correlation in use across time given our inclusion of lagged medical care use. A major concern is accurately modeling unobserved health because the health measures available in the data may not fully capture the effects of past medical care utilization through the health production function. Failing to account for unobserved heterogeneity would incorrectly attribute significance to lagged consumption behavior.

Current health and medical care inputs determine health in the subsequent period through a health production function. General health stock is a 4-category outcome represented by functional limitations, with death as the extreme negative health outcome. Using a multinomial logit model, functional status outcomes include zero ADL or IADL limitations ($H_{t+1} = 0$), at least one IADL limitation and up to two ADL limitations ($H_{t+1} = 1$), more than two ADL limitations ($H_{t+1} = 2$), and death ($H_{t+1} = 3$). The logit specification of the health production function is

[13] We include an indicator of any hospital service, physician service, and prescription drug utilization in the previous period. The index function $\mathbf{1}(\cdot)$ equals one when the endogenous previous behavior in parenthesis is true and is zero, otherwise.

$$
\begin{aligned}
\ln\left[\frac{\Pr(H_{t+1}=h)}{\Pr(H_{t+1}=0)}\right] &= \gamma_{h0}+\gamma_{h1}X_t+\gamma_{h2}H_t+\gamma_{h3}S_t \\
&\quad +\gamma_{h4}\mathbf{1}(A_t>0)+\gamma_{h5}A_t \qquad (12)\\
&\quad +\gamma_{h6}\mathbf{1}(B_t>0)+\gamma_{h7}B_t \\
&\quad +\gamma_{h8}\mathbf{1}(D_t>0)+\gamma_{h9}D_t \\
&\quad +\rho_h^H\mu+\omega_h^H\nu_t, \\
&\quad h=1,2,\ \text{and } 3.
\end{aligned}
$$

The dynamics of health are captured, in part, by the dependence of one's health stock next period on endogenous values of her health stock in the current period. The occurrence of health shocks each period also influence health stock transitions. Additionally, health transitions are dynamic because they depend on medical care consumption in the current period. Theory suggests that health production depends on utilization but not expenditures per se (Grossman, 1972). That is, consumption of medical care, not expenditures on medical care, improves, restores, or limits further deterioration in the health stock. Hence, we include indicators of any use, but examine the role of expenditures also.[14] In estimation we include interactions of general health (H_t) with each type of care (A_t, B_t, and D_t) to allow for a different productive effect of medical care at different levels of health. We include interactions of each medical care type with the other types of care to measure complementarities in input allocation. This Grossman-like dynamic health production function is essential for linking current consumption behavior with future health (and indirectly, future medical care utilization) and thus appropriately predicting net costs of expanded drug coverage.

In addition to the two insurance equations (Equations 7 and 8), one general health equation (Equation 12) and three health shock equations (Equations 9), and six medical care demand equations (Equations 10 and 11), our model is not complete without specifying equations for lagged endogenous variables (measured in the first period an individual is observed) that enter some of the dynamic equations. These include initial health, initial insurance, and initial utilization. While we observe these initial values for individuals in

[14] In the results section we provide our interpretation of the significance of expenditures and utilization in the production function.

our sample, we cannot model them as described above because we do not observe previous behavior. Hence our initial conditions represent reduced form analogues to the dynamic demand and health production equations and include appropriate variables for identification. We also include equations for existence of the four chronic conditions when we first observed individuals in our sample. Discussion of these initial equations, their dependence on the unobserved heterogeneity, and the estimated likelihood function is provided in the Appendix. There we also provide more detail about the joint estimation procedure.

3.3 Identification

Identification in this system of dynamic equations follows the arguments of Bhargava and Sargan (1983) and Arellano and Bond (1991). Estimation of dynamic equations with panel data requires exogeneity of some of the explanatory variables conditional on the unobserved individual heterogeneity. Thus, all lagged values of exogenous variables serve to identify the system. These include Z_t^H, Z_t^I, and Z_t^P, as well as time-varying individual characteristics in X_t. Similarly, conditional on the unobserved heterogeneity (μ and ν_t), lagged values of the endogenous variables also aid identification assuming there is no serial correlation in the remaining errors. Additionally, we include some exogenous variables in the reduced-form specification of the initial conditions that do not independently affect the dynamic demand and health outcome equations. These include height, which serves to measure health during childhood, and exogenous time-varying supply-side variables. Height is jointly significant in the initial condition equations, and is found to be insignificant when included in the main equations.

Our specification of the permanent and time-varying unobserved individual heterogeneity also serves to identify the system, allowing all lagged *i.i.d.* errors to independently influence current behavior (e.g., through inclusion of lagged health in the expenditure equations or the inclusion of current medical care inputs in subsequent health outcomes). That is, observed values of endogenous variables enter those equations rather than predicted values as in two-stage techniques that deal with endogeneity of explanatory variables. Finally, the functional forms of the equations are not linear in each circumstance, and hence identification is further enhanced by the non-linear nature of the specification. This non-linearity of the initial condition equations also reduces the number of identifying variables needed for identification.

4 Description of Data

The Medicare Current Beneficiary Survey (MCBS) is well suited for estimating our dynamic model. The MCBS is a longitudinal survey conducted by the Center for Medicare and Medicaid Services. Information in the MCBS is provided in two major parts—the survey files and the event files. Each respondent of the sample was surveyed three times a year and followed for multiple years. At the first interview, the respondents answered questions about their demographics, insurance and health status, including their functional status and chronic conditions. At the end of each year, usually between September and December, respondents re-answered questions about their health status to record changes in their health. The event files include the date, charge and payment information of each inpatient, outpatient, medical provider, nursing home, home health and hospice event since the first interview and is based on claims data. The charge and payment information of each prescription or refill are also recorded, but the exact date of each prescription or refill is not available.

Our study uses the MCBS files from 1992 to 2001. As part of a longitudinal survey, the respondents were followed for several years. This longitudinal feature of MCBS makes it possible to estimate the effect of drug utilization in one year on subsequent health outcomes and medical care utilization in the next year. Additionally, new elderly individuals (age 65 and older) were brought into the survey each year allowing the sample size and composition to be relatively similar across time. However, not all of the respondents in the sample are observed for the same number of years. Differences in length of participation are due to sample design and death; there is relatively little attrition due to non-response.[15] However, because expenditures on outpatient prescription drugs are not available from the MCBS for people who lived in long-term care facilities, we do not include them in analysis. Of the 28,906 elderly individuals surveyed between 1992 and 2001, 2941 were dropped because they were either continuously enrolled in a nursing home, or entered a nursing home during the

[15] Respondents in early years of the survey were followed for five years; more recent participants were followed for two or three years.

period of observation.[16] Table 1 details information on the sample of 25,935 men and women who contribute 76,321 person-year observations to our analyses.

Measurement of health stock should reflect true health as accurately and broadly as possible. Rather than use subjective self-reported health, we select the more objective measures of functional status. In the MCBS, a survey of functional status is conducted between September and December in every calendar year. About 40% of the sample respondents report some functional limitation at some point during the survey period. Almost 30 percent report moderate disability measured by difficulty with at least one Instrumental Activities of Daily Living (IADL) and with no more than two Activities of Daily Living (ADL). Severe disability, measured by difficulty with three or more ADLs, affects about 10 percent of the sample. Death rates average about five percent and rise with age (as seen in Figure 1) and deterioration in health. The top panel of Table 2 details one-year health transitions of the elderly over the sample period. This table highlights the extent of movement across health categories; obviously the transition rates differ by age and other characteristics. About 40% of the elderly remain in a given health state from one year to the next. However, transitions to poorer health are common. Death, for example, is more probable as functional limitations increase with 14% of the severely disabled dying in a given year. Interestingly, the incidence of health improvement is also significant. Almost 20% of the sample experiences improved health from one year to the next.

The bottom panel of Table 2 summarizes the probability of health shocks conditional on ever experiencing a particular chronic condition. Upon initial observation, individuals report whether they have ever had cardiovascular or cerebrovascular disease (denoted heart or stroke), respiratory disease, cancer, or diabetes. In each year surveyed, the individual may experience medical claims associated with the first three of these diseases. We define such claims to indicate a particular health shock in that year. Hence we are able to capture both the onset of chronic conditions as well as complications associated with existing conditions.

[16] Those who entered a nursing home amount to 5.8% of the elderly sample. If medical expenditures of these individuals is higher and health is worse (relative to those who are not institutionalized) prior to entering a nursing home, then our conclusions represent underestimates of both the costs and benefits of insuring drug coverage. However, logistically, we cannot glean from the survey whether a nursing home admission is a short-term stay or long-term residence for many individuals (e.g., those who enter in the last year they are surveyed) and hence, do not model this form of attrition.

Case and Paxson (2004) find that differences in morbidity and mortality across genders can be explained by differences in the distribution of chronic conditions.

Table 3 describes the distribution of dependent variables, along with notation and specification of each equation in the set of jointly estimated equations. The sources of major supplemental insurance for Medicare beneficiaries are Medicaid, employer-provided and privately purchased insurance (private plans), and the Medicare managed care option. In order to measure the effect of third-party coverage of drugs, we group private plans and managed care insurance by whether or not the plan offers outpatient prescription drug coverage. Thus, as explanatory variables, supplemental insurance includes five dummy variables indicating whether the Medicare beneficiary has Medicaid, a private plan with a drug benefit, a private plan without a drug benefit, managed care with a drug benefit, and managed care without a drug benefit. About 13% of the Medicare-covered sample respondents were dually covered by Medicaid, which covers prescription drug medication. Almost 50% of the sample respondents received some other form of supplemental insurance with a drug benefit. Yet, over one-third of the elderly have no prescription drug coverage.

The average annual outpatient prescription drug expenditure (conditional on any) was \$980 over the 1992-2001 period.[17] Although the observed probability of prescription drug use by age is nearly constant, expenditures, if any, gradually fall (see Figure 2).[18] This simple graph illustrates the complex relationship between medical care use and age. One might expect expenditures to rise with age because health is likely to be deteriorating. However, those individuals who survive to older ages may be healthier reflecting a negative relationship between medical care expenditures and age among survivors.

Figure 3 illustrates similar patterns of Part A inpatient expenditures (conditional on any) with age (mean: \$13,058). However, the probability of hospitalization increases dramatically with age from around 12% at age 65 to over 30% at ages above 90. The lower average hospital expenses as individuals age suggest that the stays of older patients may be shorter than those of younger patients. This may be due to higher death rates or reflect the less aggressive treatment of those who are hospitalized at older ages. Utilization of Part B

[17] We adjust all expenditures and income in the sample to year 2001 dollars using the Consumer Price Index.

[18] Diamonds represent the observed statistics from the actual sample; we discuss simulated observations indicated by circles later.

physican services is uniform by age, as shown in Figure 4, but annual expenditures by age exhibit the similar inverted U-shaped pattern. On average, these expenditures, if any, are $2,013.

It is well known that a large proportion of elderly health care expenditures in the U.S. is consumed by individuals in their last year of life. Figure 5 illustrates, by age, the higher average annual expenditures for hospital and physician services among those in their death year and those who do not die that year. The differences are more striking for individuals who die at earlier ages. Interestingly, outpatient prescription drug use is lower for those who die relative to survivors. These deceased individuals obviously have fewer days within the year to consume drugs and may be hospitalized more days out of the year (and receiving inpatient drug treatment).

Table 4 summarizes additional variables used to explain insurance selection, medical care demand, health shocks, and health stock transitions. In addition to these exogenous variables, the dependent variables defined in Table 3 serve as endogenous explanatory variables in relevant equations. Most of the explanatory variables vary across time. We include several variables to capture variation in the supply and price of insurance and medical care during our sample period. These include the number of physicians, hospitals, and hospital beds per 1000 elderly by county and year, obtained from the Area Resource File. This data source also provides the adjusted average per capita cost (AAPCC) rates for Medicare services, which is based on projected average county-level fee-for-service spending for each upcoming year. Retail prescription drug prices vary by state and year. We also include an indicator of whether the elderly person lives within 100 miles of the Canadian or Mexican borders since drugs are relatively cheaper in these non-U.S. locations. Managed care penetration (or number of HMOs enrollees per capita) reflects availability of different types of insurance coverage as well as prices of medical care services in particular markets. We include the Environmental Protection Agency's measure of median air quality by county and year, where increasing values of the index indicate lower air quality, to capture changes in exogenous measures that may influence health. As a representative sample of aging Medicare beneficiaries, the average age of the sample is 75 years. Sixty percent of the sample are female. Over half of the respondents are married, and almost 40 percent are widowed.

Minority populations account for 12 percent of the entire sample, and 27 percent of the sample live in a rural area.

5 Results

5.1 Estimation Results

The interpretation of results is difficult in this dynamic system of demand equations and health production with its feed-forward structure. First we discuss the signs and significance of the main explanatory variables of interest in each equation, which qualitatively describes the short-run effects.[19] In section 5.2 we discuss simulation results to illustrate the influence of particular variables in the long run, taking into account changes in health status and mortality.

Effects of insurance on medical care demand

We begin by discussing the effect of insurance on prescription drug consumption, since this relationship is at the heart of our analysis and is an object of policy concern. In our preferred model that controls for endogeneity (i.e., the jointly estimated set of correlated equations henceforth labeled *multiple equations with unobserved heterogeneity*), drug coverage, and supplemental insurance of any kind, has a significant positive effect on whether a person purchases any prescription drugs (Table 5a, second column) and the (log) level of expenditures for those who purchase any (Table 5a, fourth column). The signs of coefficients on other variables are generally in the expected direction, with functional limitations, chronic conditions, and current health shocks each increasing utilization of and expenditures on prescription drugs.

Drug coverage, specifically, has little influence on the probability or (log) level of hospital expenditures (see Table 5b, second and fourth columns). Interestingly, however, the Medicare managed care plan is associated with a greater probability of hospitalization, but lower expenditures among those with any inpatient stay. This relationship supports the efforts by managed care organizations to reduce medical care costs among its members by such

[19]Estimated coefficients and standard errors for all explanatory variables in each jointly estimated equation are available by request from the authors.

means as early detection and controlled spending. Health shocks have a large positive effect on hospital services consumption. Disability is associated with more hospital care. Supplemental insurance of all types increases physician services consumption, except managed care coverage (Table 5c, second and fourth columns). Again we see reductions in utilization and expenditures among those who select the Medicare managed care option. The influence of disability, health shocks, and chronic conditions is positive and significant.

To understand the bias stemming from unobserved heterogeneity that is eliminated with our preferred approach, it is necessary to compare the marginal effects of particular variables from our jointly estimated system of equations with those produced by estimating the equations independently (i.e., separate estimation of uncorrelated equations henceforth labeled *single equation without unobserved heterogeneity*). The alternative estimation approach treats previous behavior, health, and insurance as exogenous and hence does not account for correlation in individual unobservables across time or between contemporaneous endogenous variables. The extent of the bias is not easily determined by comparing coefficients; thus, we simulate behavior using both models in order to evaluate the role of heterogeneity in purging the estimates of bias. However, differences in the size and significance of particular variable effects is evident.

In modeling the permanent and time-varying individual unobserved heterogeneity that is likely to influence insurance, expenditures, and health, we found three mass points to be sufficient to capture the distribution of permanent heterogeneity, and three mass points for time-varying heterogeneity. (Estimation with more mass points for either discrete distribution did not improve the fit of the model.) The estimated loadings are positive in most cases where they are significant, suggesting that individuals with unobserved characteristics to the right of the distribution are more likely to use that medical service and to spend more on it (see last two rows of Tables 5a through 5c). The time-varying heterogeneity exhibits significance uniformly in these demand equations, whereas the permanent heterogeneity is often insignificant. We interpret this pattern to suggest that our measures of health are good predictors of general health, and that the time-varying heterogeneity serves to pick up unobserved or omitted health shocks that alter per-period demand. This importance of time-varying heterogeneity supports a main feature of our model (i.e., joint estimation of medical care demand equations).

Effects of medical care consumption on health production

We turn now to coefficient estimates on variables that influence health production (Tables 6a-6c). The importance of modeling this equation jointly with the expenditure equations (and health shocks) is to capture correlation in the error terms associated with health outcomes and endogenous medical care inputs that affect health. Such correlation is confirmed if the marginal effects of the endogenous inputs differ when heterogeneity is modeled and when it is not. With the caveat that specific parameter estimates are hard to compare, we find sizable differences in the estimates for each health outcome relative to no functional limitation.

Increases in prescription drug expenditures, if any, reduce the probability of death. This effect is greater for those who are moderately disabled and when used in combination with other types of medical care. In general, combinations of the different medical care inputs have a productive effect on health, suggesting that they are complements. Notice also that while inpatient and physician services expenditures appear to reduce health (i.e., increase the probability of being in the worse health state), this effect is moderated (where significant) for individuals with greater functional limitations. If we believe that differences in expenditures reflect differences in consumption levels only, then additional medical care use may maintain current health levels or prevent transitions to worse health. However, we recognize that higher expenditures may reflect differences in quality.

The positive sign on the permanent heterogeneity factor loadings is consistent with the notion of unobserved bad health. The negative time-varying factor coefficients indicate reduced probabilities of falling into worse health from one period to the next. This is not inconsistent with the interpretation of lower unobserved time-varying health in the demand equations (if we had to attempt to label it) as the latter may reflect unobserved health shocks that lead to temporary health declines among generally healthier people. We contend that another feature of our model (i.e., joint estimation of endogenous medical care inputs and health outcomes) is warranted.

Effects of previous medical care consumption on current consumption

Next, we investigate the impact of lagged medical care use on current expenditures. Serial correlation in use as well as expenditures requires that permanent unobserved heterogeneity be modeled if we do not want to incorrectly assume that previous behavior causes current behavior. Differences in point estimates between a model with and without this heterogeneity demonstrate the importance of modeling the endogeneity of past use. In Table 5a, for example, we find that lagged medical care use affects medical care consumption today. Previous prescription drug and physician services use are positively serially correlated with contemporaneous drug use, while lagged hospitalization suggests a lower probability of any drug use, but greater expenditures if any. Individuals who have been hospitalized or used physician services in the previous year are more likely to be hospitalized this year (Table 5b), but prescription drug consumption appears to reduce the need for hospital services in the subsequent year. Prescription drug use in the previous year is highly positively correlated with demand for physician services in the current year. These estimates suggest that previous use has a direct effect on current use independent of its indirect effect through changes in health. We have attempted to adequately capture health with both the observed measures of health and the unobserved heterogeneity. If our efforts have been unsuccessful then lagged expenditures may, in part, reflect true health. We maintain, however, that our results confirm importance of this feature of our preferred model (i.e., direct effects of lagged behavior). These findings will have significant effects on the long-run cost projections associated with a Medicare drug benefit.

Coefficient estimates on selected variables describing supplemental insurance selection, prescription drug coverage, and health shocks are provided in Tables 7, 8, and 9. The influence of unobserved heterogeneity in the supplemental insurance equations suggests that those in worse health are more likely to be on Medicaid and less likely to be privately insured. It also suggests, however, that the unobserved heterogeneity may be associated with socioeconomic unobservables. To help understand the role of these endogenous variables on expenditures and health over time, we quantify the effects of the dynamic, feed-forward behavior that we model in section 5.2.

We demonstrate the fit of our preferred model by comparing observed outcomes of the sample with model predictions using estimated model parameters and observed explanatory variables. In Table 10, we summarize observed outcomes *by year* and report predictions from our model simulation using the updated values of endogenous regressors. Figure 1 depicts how well our model (indicated by circles) fits the observed MCBS mortality rate (indicated by diamonds). Comparisons of observed and predicted prescription drug use and expenditures, hospitalization rates and expenditures, and physician services use and expenditures *by age* are depicted in Figures 2, 3, and 3. The model fits these outcomes well, bearing in mind that the sample size gets relatively small at ages above 90. We also compare our model's predictions of medical care demand with that from the observed data for individuals in their death year. Figure 5 indicates that our model captures the observed fact that expenditures differ considerably among these two groups of elderly. We conjecture that the model is able to do so given its rich specification of endogenous health stock and stochastic health shocks.

5.2 Simulation of Drug Coverage

The effect of drug coverage on medical care expenditures and health in this nonlinear dynamic model is best shown with simulations. The simulations quantify the long-run effect of drug coverage by incorporating the dynamic effects of behavior on future medical care choices and health transitions. To answer the policy question of how expansion of prescription drug coverage to all elderly Medicare beneficiaries would affect medical care expenditures, we choose a five-year period. This is long enough to demonstrate the importance of a dynamic model but not so long as to simulate beyond our data. We simulate expenditures and health transitions under four different drug coverage scenarios: no supplemental insurance beyond Medicare (i.e., no drug coverage), coverage by Medicaid, coverage by private insurance with a drug benefit, and coverage by Medicare managed care with a drug benefit. We show results from models that do and do not control for unobserved heterogeneity.

The simulation procedure is straightforward. We use the estimated model to simulate health shocks and demand for prescription drugs and Medicare Part A and B services for the entire sample of 25,935 individuals given their initially observed characteristics. Supplemental health insurance is not simulated because it is fixed as part of each policy simulation.

We use these simulated input choices and health shocks and the estimated health production function to update end-of-period health. This simulated health outcome is then transferred to the next period and chronic conditions are updated to reflect any health shocks during the period. Conditional on the updated health and previous (simulated) expenditures, expenditures and current health shocks are again simulated. Given these, the health stock is simulated and chronic conditions updated. This process can be repeated for any number of years. We use the simulated values of all endogenous right-hand side variables but retain the observed (in the original data) values of exogenous variables (e.g., age, marital status, rural residency, supply-side variables, etc.).[20] We generate 400 replications of each individual allowing, per replication, one draw from the permanent unobserved heterogeneity distribution for the five-year period and draws every year from the time-varying distribution. Predicted probabilities of any expenditure of each type (i.e., prescription drug, hospital, and physician services) and health outcomes (i.e., shocks and stock) are mapped to the unit interval and a uniform random variable determines the simulated outcome. Normally distributed random numbers reflecting the estimated standard error are added to predicted log expenditures and expenditure outcomes in levels are calculated. To evaluate different types of prescription drug coverage, the simulations are repeated using the same random numbers (for determination of unobserved heterogeneity and endogenous outcomes) but drug coverage from one of the four sources (i.e., Medicare only (no drug coverage), Medicaid, private insurance with drug coverage, and Medicare HMO with drug coverage) is assigned to all individuals and does not vary over the five-year simulation.

The use of our preferred dynamic model with unobserved heterogeneity suggests that drug coverage increases prescription drug expenditures over a five-year period by 20 to 35 percent depending on the source of coverage (see top half of Table 11).[21] The static model without heterogeneity suggests a larger average range of the increase in drug expenditures from 16 to 58 percent. Recall that estimation of the static model does not account for

[20] In instances where individuals are simulated to survive (beyond the years we observe them) we assume that the exogenous individual values (such as marital status and rural residency) are the same as the last observed period. We use the corresponding current year values of exogenous supply-side variables based on the individual's last observed county or state of residence.

[21] The expenditures are averaged over time and over survivors in each year.

dynamics in behavior and produces biased estimates of the effect of insurance since unobservables correlated with both the insurance choice and expenditures or health outcomes are not modeled. In contrast to the substantial increase in drug expenditures, Part A expenditures increase about 10% over five years with private or HMO coverage, but actually decrease with Medicaid coverage. Interestingly, Part B expenditures are 34% larger on the Medicaid and private plans, but fall by 47% with the HMO plan. These responses reflect both substitution/complementarity between different types of medical care as well as changes in health over time. The differential responses across plans, however, suggest that something unique to each type of insurance plays a role in total medical care consumption. For example, private coverage may induce greater consumption of all services (e.g., prescription drug use requires physician consultation and follow-up) whereas managed care insurance seeks to control medical care use. In total, expenditures increase by 14 and 23% with Medicaid and the private plan respectively, but fall slightly when all individuals are covered by Medicare's managed care plan with drug benefits. The static model without heterogeneity predicts that changes in these expenditures would be over twice as large. Our preferred model indicates that prescription drug coverage from all sources leads to increases in survival probabilities relative to coverage by Medicare only. In each case, however, the distribution of health among survivors is shifted to worse health. The changes in survival and the health distribution among survivors are larger in the static model without heterogeneity, reflecting the biases implied by failure to jointly model all correlated outcomes over time.

In an effort to further understand the effects of prescription drug coverage on health outcomes and medical care expenditures, we decompose the changes in medical care consumption and the resulting health outcomes by survival status. *Sole survivors* are those individuals who live regardless of the drug benefit structure. *Marginal survivors* would have died if no drug benefit were available. Put differently, marginal survivors survive longer when either a Medicaid, private, or HMO drug benefit is available. As expected, sole survivors are healthier in year one than marginal survivors (see top panel of Table 12). They are younger, more likely to be female, and have fewer functional limitations or chronic conditions. Although differences in age and health at baseline between these two groups explain some of the differences in health outcomes, we see that supplemental drug coverage results in very different medical care responses across the two groups. Unconditional on type of drug coverage, the sole survivors increase their drug consumption a moderate amount (≈27%), and experience a slight increase in hospital expenditures. The marginal survivors, however, triple their expenditures on drugs, and consume significantly more hospital services. Interestingly, physician services use among those with HMO coverage drops for both groups, relative to the increases in Part B expenditures for the Medicaid and private insurance simulations across the two groups. In both instances, however, expenditures of the marginal survivors is quite different. These expenditure differences (averaged over the surviving years) are the result of increased survival years of the marginal group, but also reflect the lowered health status of these survivors.

The effect of drug coverage on long-run behavior is also evident in Table 13 where we report changes in five-year expenditures in each service category by whether the health of sole survivors improved, was maintained, or deteriorated. While the direction of expenditure change across insurance plans and type of medical care is the same for all health categories, it appears that the expenditures of individuals whose health deteriorated were lower than that of those whose health improved or stayed the same. Put differently, those who increased their spending more (with drug coverage than without) had better health outcomes. This finding reflects the productive effect of medical care as an input to health production.

The results in Tables 11, 12, and 13 account for dynamic changes in behavior over time. That is, they reflect the per-period simulated and updated choices, rather than the observed sample values of endogenous explanatory variables. In order to compare our results to those from static models that do not account for the dynamic effects nor the unobserved heterogeneity likely to influence behavior, we report the effects of each type of insurance coverage on expenditures in the *first* year of simulation. Hence, we can isolate the omission of dynamic behavior from the omission of unobserved heterogeneity. The bias eliminated by the modeling of unobserved heterogeneity is apparent in Table 14 by comparing the two different estimation procedures. Comparisons of the top panel of Table 14 with Table 11 demonstrate the effects of dynamic health outcomes and lagged expenditure behavior on five-year expenditures.

6 Discussion

Our study of elderly health dynamics has produced several important policy-relevant and methodological findings. In the policy area, we have three notable findings. First, the simulation results suggest that a prescription drug benefit will increase the demand for prescription drugs over a five-year period by an average of between 20 and 35 percent. Second, drug coverage decreases the mortality rate of elderly persons, which leads to an observed increase in the average disability rate among survivors. For healthier persons, prescription drugs may help improve their health status slightly; for those in worse health, prescription drugs may reduce their mortality rate. Third, the type of insurance coverage matters. Medicaid and private prescription drug coverage increases the demand for hospital care and physician services, largely due to increased longevity. Furthermore, individuals with managed care experience lower physician service expenditures, without significant differences in health outcomes.

In terms of methods, our study contributes three important ideas. First, our study goes beyond looking at the effect of drug policy on the demand for drugs only, and investigates the dynamic effects of insurance and drug coverage on Medicare beneficiaries' health and other Medicare-covered service expenditures. Second, our study provides evidence that health care behavior of the elderly is correlated over time, and that the significance of this relationship depends on both permanent and time-varying unobserved heterogeneity. Third, our study produces both short-term and long-run predictions that illustrate the dynamic effects of prescription drug coverage on total Medicare expenditures and on the health status of Medicare beneficiaries.

Returning to the general question of how health insurance affects health expenditures, our study vividly shows how health insurance for one type of medical care creates an additional change in medical care consumption behavior beyond simple moral hazard. Prescription drug insurance changes the relative out-of-pocket price of different types of therapies that may also have different relative effectiveness. The simulations not only show evidence of simple moral hazard, with an increase in prescription drug use, but also show changes in expenditures for other types of medical care over time. Thus, our study demonstrates the practical importance of this theoretical issue. McFadden (2006) explained that for Medicare Part D, moral hazard is a bigger issue than adverse selection. This moral hazard issue, we argue, is more complex than in standard insurance problems.

References

Adams, A.S., Soumerai, S.B. and Ross-Degnan, D. "The Case for a Medicare Drug Coverage Benefit: A Critical Review of the Empirical Evidence." *Annual Review of Public Health*, 2001a, 22, pp. 49-61.

_____. "Utilization of Antihypertensive Drugs among Medicare Enrollees." *Health Affairs*, 2001b.

Angeles, Gustavo, Guilkey, David, and Mroz, Thomas A. "Purposive Program Placement and the Estimation of Family Planning Program Effects in Tanzania." *Journal of the American Statistical Association*, 1998, 93(443), pp. 884-899.

Arellano, M. and Bond S. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, 1991, 58, pp. 277-297.

Becker, Gary and Murphy, Kevin. "A Theory of Rational Addiction." *American Economic Review*, 1988, 96, pp. 675-700.

Becker, Gary, Michael Grossman, and Kevin Murphy. "An Empirical Analysis of Cigarette Addiction." *American Economic Review*, 1994, 84, pp. 396-418.

Bhargava, A. and Sargan, J.D. "Estimating Dynamic Random Effects Models From Panel Data Covering Short Time Periods." *Econometrica*, 1983, 51(6), pp. 1635-1659.

Blau, David and Gilleskie, Donna "Retiree Health Insurance and Labor Force Behavior of Older Men in the 1990's." *Review of Economics and Statistics*, 2001, 83(1), pp. 60-84.

Blau, David and Hagy, Alison "The Demand for Quality in Child Care." *Journal of Political Economy*, 1998, 106(1), pp. 104-146.

Blustein, J. "Drug Coverage and Drug Purchases by Medicare Beneficiaries with Hypertension." *Health Affairs*, 2000, 19, pp. 219-30.

Case, Anne and Paxson, Christina "Sex Differences in Morbidity and Mortality." Working paper, 2004.

Crawford, Greg and Shum, Matthew. "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica*, 2005, 73(4), pp. 1135-1174.

Cutler, David. "The Incidence of Adverse Medical Outcomes under Prospective Payment." *Econometrica*, 1995, 63(1), pp. 29-50.

Cutler, David. "Declining Disability among the Elderly." *Health Affairs*, 2001, 20(6), pp. 11-28.

Davis, Morris and Foster, E. Michael. "A Stochastic Dynamic Model of the Mental Health of Children," *International Economic Review*, 2005, 46(3), pp. 837-866.

Federman, A.D., Alyce, S.A., Ross-Degnan, D., Sourmerai, S.B. and Ayanina, J.Z. "Supplemental Insurance and Use of Effective Cardiovascular Drugs among Elderly Medicare Beneficiaries with Coronary Heart Disease." *JAMA*, 2001, 286(14), pp. 1732-39.

Ferrucci, L. and Guralnik, J. "Hospital Diagnoses, Medicare Charges, and Nursing Home Admissions in the Year When Older Persons Become Severely Disabled." *JAMA*, 1997, 277, pp. 728-34.

Fillenbaum, G.G., Hanlon, J.T., Corder, E.H., Ziqubu-Page, T., Wall, W.E. and Brock, D. "Prescription and Nonprescription Drug Use among Black and White Community-Residing Elderly." *American Journal of Public Health*, 1993, 83, pp. 1577-1582.

Goldman, Dana. "Managed Care as a Public Cost Containment Mechanism." *RAND Journal of Economics*, 1995 , 26(2), pp. 277-295.

Gilleskie, Donna. "A Dynamic Stochastic Model of Medical Care Use and Work Absence." *Econometrica*, 1998, 66(1), pp. 1-45.

Gowrisankaran, Gautum and Town, Robert J. "Managed Care, Drug Benefit and Mortality: An Analysis of the Elderly." NBER Working Paper No. 10204, 2004.

Grossman, Michael. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy*, 1972, 80(2), pp. 223-255.

Heckman, James and Singer, Burton. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica*, 1983, 52, pp. 271-320.

Hoynes, Hilary. “Welfare Transfers in Two-parent Families: Labor Supply and Welfare Participation under AFDC-UP.” *Econometrica*, 1996, 64(2), pp. 295-332.

Hu, W. “Child Support, Welfare Dependency, and Women’s Labor Supply.” *Journal of Human Resources*, 1999, 34(1), pp. 71-103.

Johnson, R.E., Goodman, M.J., Hornbook, M.C. and Eldredge, M.B. “The Impact of Increasing Patient Prescription Drug Cost-Sharing on Therapeutic Classes of Drugs Received and on the Health Status of Elderly HMO Members.” *Health Services Research*, 1997, 32, pp. 103-22.

Keeler, Emmett, Newhouse, Joseph, and Phelps, Charles. “Deductibles and the Demand for Medical Care Services: The Theory of a Consumer Facing a Variable Price Schedule under Uncertainty,” *Econometrica*,1977, 45, pp. 641-655.

Khwaja, Ahmed. “Health Insurance, Habits and Health Outcomes: A Dynamic Stochastic Model of Investment in Health,” Ph.D. Dissertation, University of Minnesota, 2001.

Lichtenberg, Frank. “The Economic and Human Impact of New Drugs.” *Journal of Clinical Psychiatry*, 2003, 64, pp. 15-18.

_____. “The Impact of New Drug Launches on Longevity: Evidence from Longitudinal Disease-Level Data from 52 Countries, 1982-2001.” NBER Working Paper No. W9754, 2003.

Lillard, Lee, Rogowski, Jeanette, and Kington, R. “Insurance Coverage for Prescription Drugs: Effects on Use and Expenditures in the Medicare Population.” *Medical Care*, 1999, 37, pp. 926-36.

Long, S.H. “Prescription Drugs and the Elderly: Issues and Options.” *Health Affairs*, 1994, 13, pp. 157-74.

Mays, Glen and Norton, Edward C. “Managed Care Contracting and Medical Care for the Uninsured: Untangling Selection from Production.” *Health Services and Outcomes Research Methodology*, 2000, 1(3–4), pp. 305–334.

McFadden, Daniel “Free Markets and Fettered Consumers.
American Economic Review, 2006, 96(1), pp. 5-29.

Mello, M., Stearns, Sally, and Norton, Edward C. "Do Medicare HMOs Still Reduce Health Services Use after Controlling for Selection Bias?" *Health Economics*, 2002, 11, pp. 323–340.

Mroz, Thomas A. "Discrete Factor Approximation in Simultaneous Equation Models: Estimating the Impact of a Dummy Endogenous Variable on a Continuous Outcome." *Journal of Econometrics*, 1999, 92, pp. 233-74.

Poisal, J.A. and Murray, L. "Growing Differences between Medicare Beneficiaries with and without Drug Coverage." *Health Affairs*, 2001, 20(2), pp. 75-85.

Poisal, J.A., Murray, L.A., Chulis, G.S. and Cooper, B.S. "Prescription Drug Coverage and Spending for Medicare Beneficiaries." *Health Care Financing Review*, 1999, 20(3), pp. 15-25.

Reeder, C.E. and Nelson, A.A. "The Differential Impact of Copayment on Drug Use in a Medicaid Population." *Inquiry*, 1985, 22, pp. 396-403.

Rogowski, Jeanette, Lillard, Lee, and Kington, R. "The Financial Burdens of Prescription Drug Use among Elderly Persons." *Gerontologist*, 1997, 37, pp. 475-82.

Soumerai, S.B., Avorn, J., Ross-Degan, D. and Fortmaker, S. "Payment Restrictions for Prescription Drugs under Medicaid: Effect on Therapy, Cost, and Equity." *New England Journal of Medicine*, 1987, 317, pp. 550-56.

Soumerai, S.B., McLaughlin, T.J., Ross-Degnan, D., Casteris, C.S. and Bollini, P. "Effects of Limiting Medicaid Drug-Reimbursement Benefits on the Use of Psychotropic Agents and Acute Mental Health Services by Patients with Schizophrenia." *New England Journal of Medicine*, 1994, 331, pp.650-655.

Soumerai, S.B. and Ross-Degnan, D. "Experience of State Drug Benefit Program." *Health Affairs*, 1990, 9, pp. 36-54.

_____. "Inadequate Prescription Drug Coverage for Medicare Enrollees–a Call to Action." *New England Journal of Medicine*, 1999, 340(9), pp. 722-28.

Soumerai, S.B., Ross-Degnan, D., Avorn, J., McLaughlin, T.J. and Choodnovskiy, I. "Effects of Medicaid Drug-Payment Limits on Admission to Hospitals and Nursing Homes." *New England Journal of Medicine*, 1991, 325, pp.1072-1077.

Stearns, Sally, Norton, Edward C., and Yang, Zhou "Disability Offsets in the Expenditure Trade-Off between Age and Proximity to Death." Working paper, 2006.

Steinman, M.A., Sands, L.P. and Covinsky, K.E. "Self-Restriction of Medications Due to Cost in Seniors without Prescription Coverage: A National Survey." *Journal of General Internal Medicine*, 2001, 16, pp. 793-99.

Stuart, B. and Coulson, N.E. "Dynamic Aspects of Prescription Drugs Use in an Elderly Population." *Health Services Research*, 1993, 28, pp. 237-64.

_____. "Use of Outpatient Drugs as Death Approaches." *Health Care Finance Review*, 1994, 15, pp. 63-82.

Stuart, B. and Grana, J. "Are Prescribed and over-the-Counter Medicines Economic Substitutes? A Study of the Effects of Health Insurance on Medicine Choices by the Elderly." *Medical Care*, 1995, 33, pp. 487-501.

Tamblyn, R., Laprise, R., Hanley, J.A., Abrahamowicz, M., Scott, S., Mayor, N., Hurley, J., Grad, R., Latimer, E., Perreault, R., et al. "Adverse Events Associated with Prescription Drug Cost-Sharing among Poor and Elderly Persons." *JAMA*, 2001, 285(4), pp. 421-29.

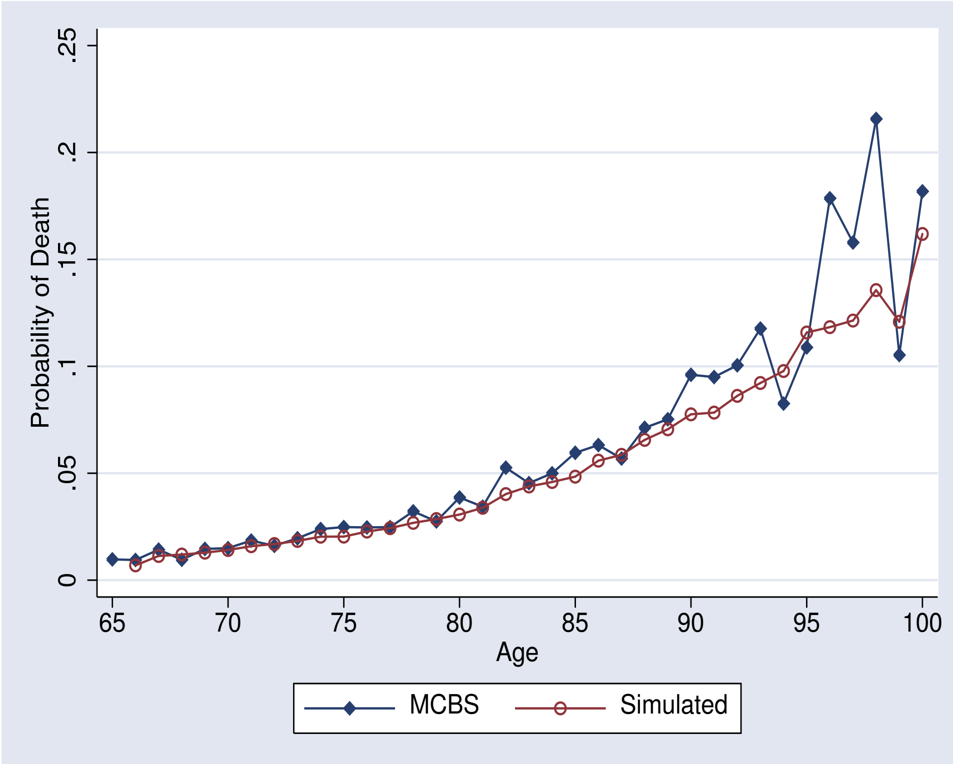

Figure 1: Actual and Simulated Annual Mortality Rate, by Age

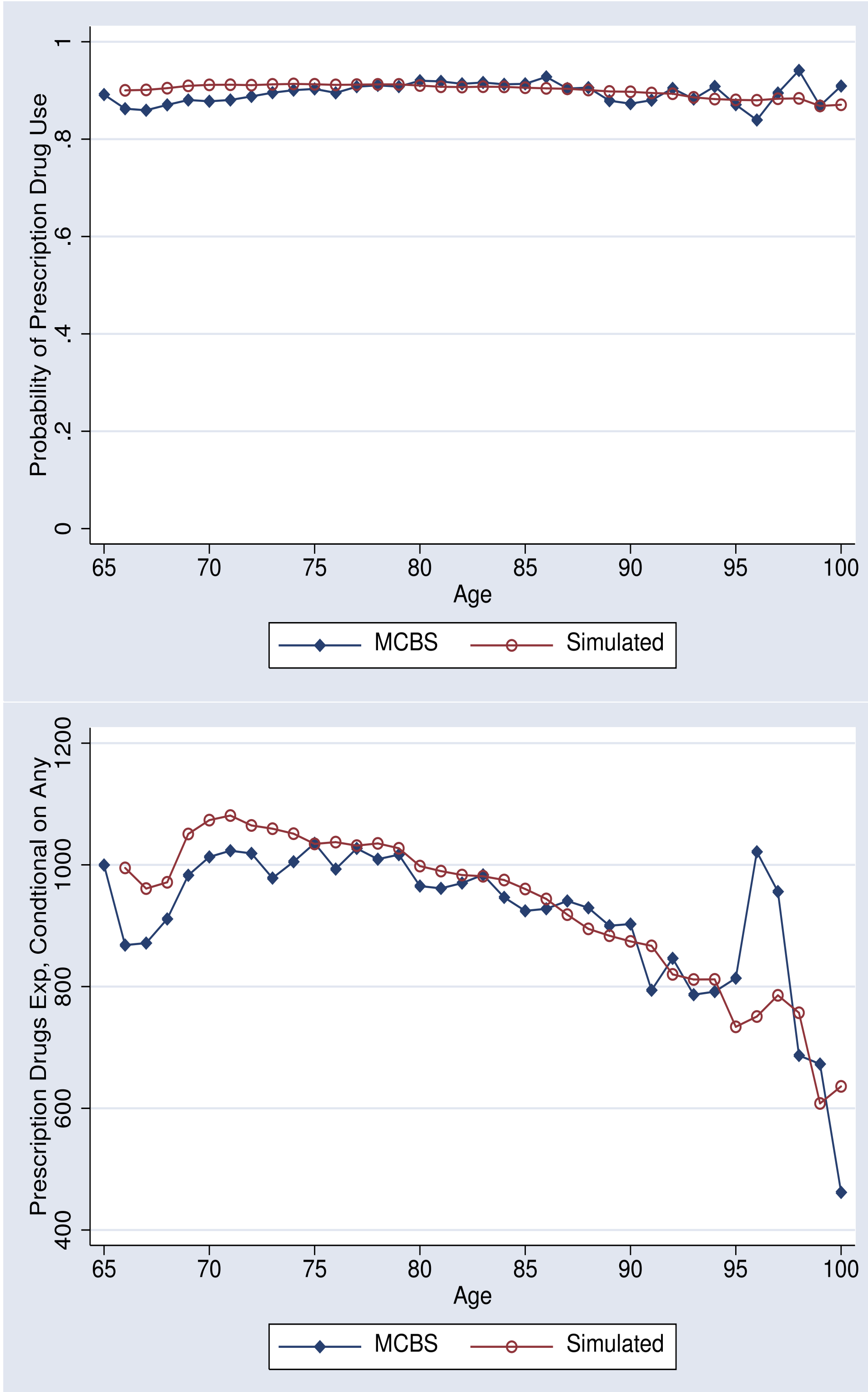

Figure 2: Actual and Simulated Prescription Drug Use and Expenditures, by Age

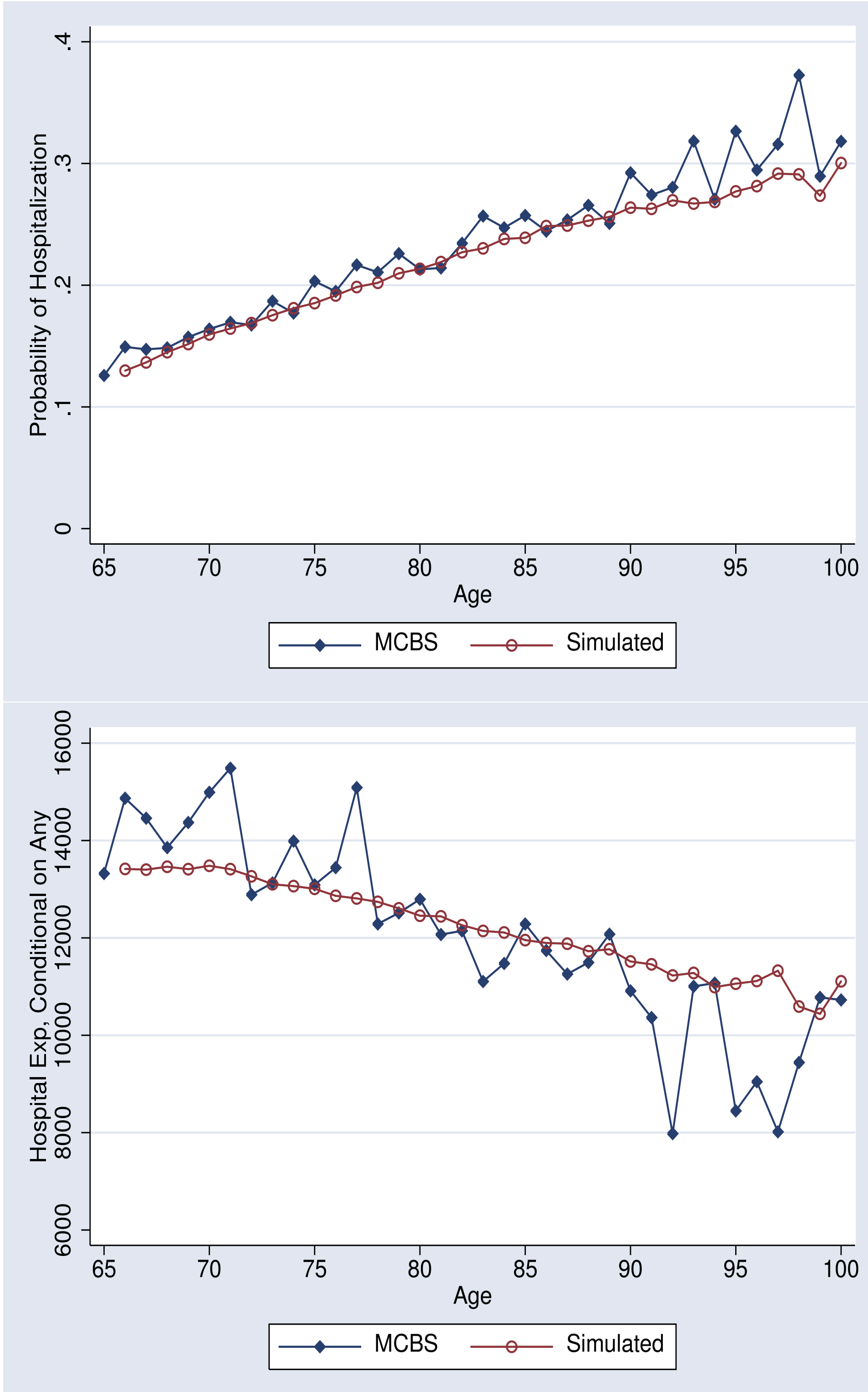

Figure 3: Actual and Simulated Inpatient Hospital Use and Expenditures, by Age

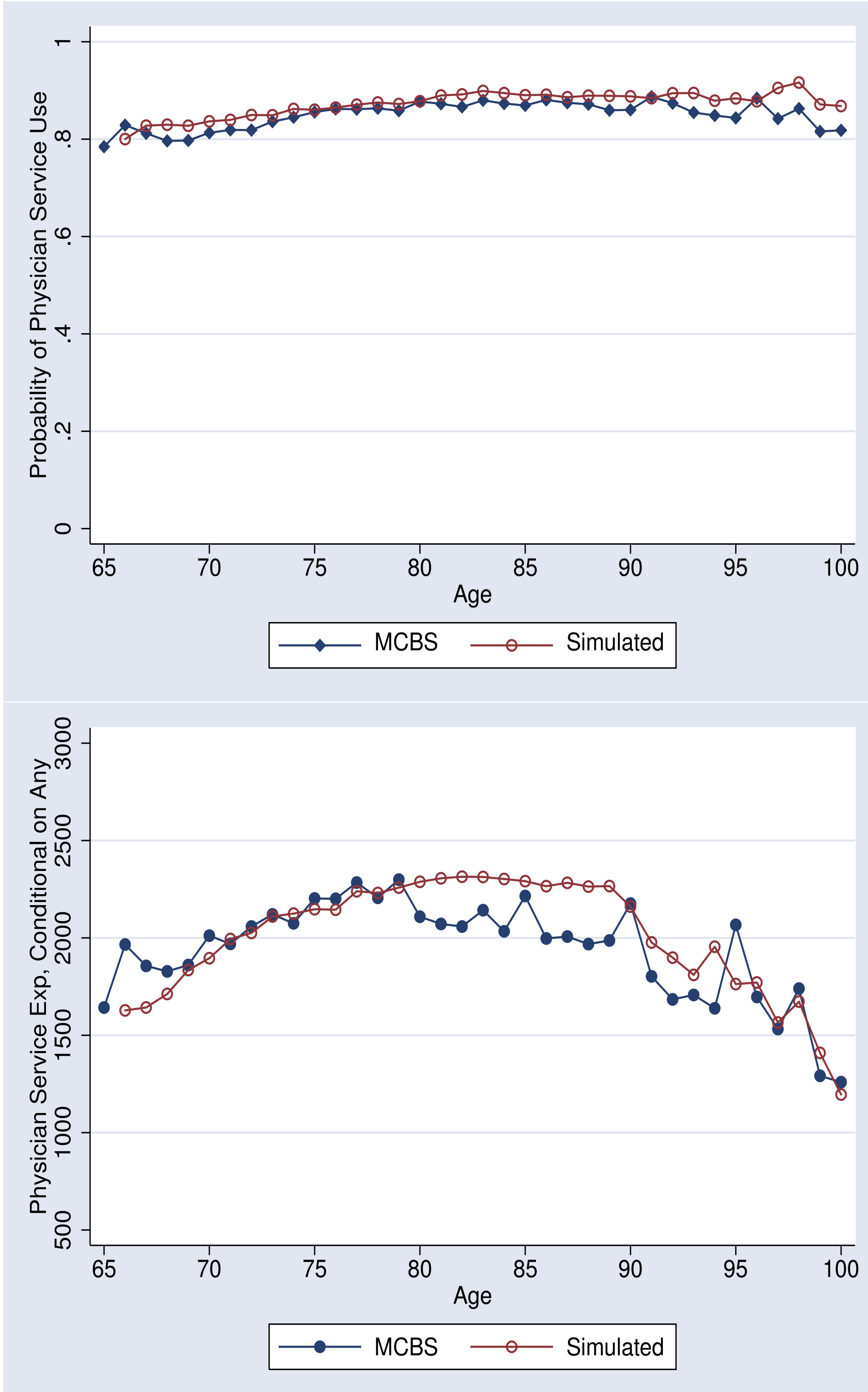

Figure 4: Actual and Simulated Physician Service Expenditures, by Age

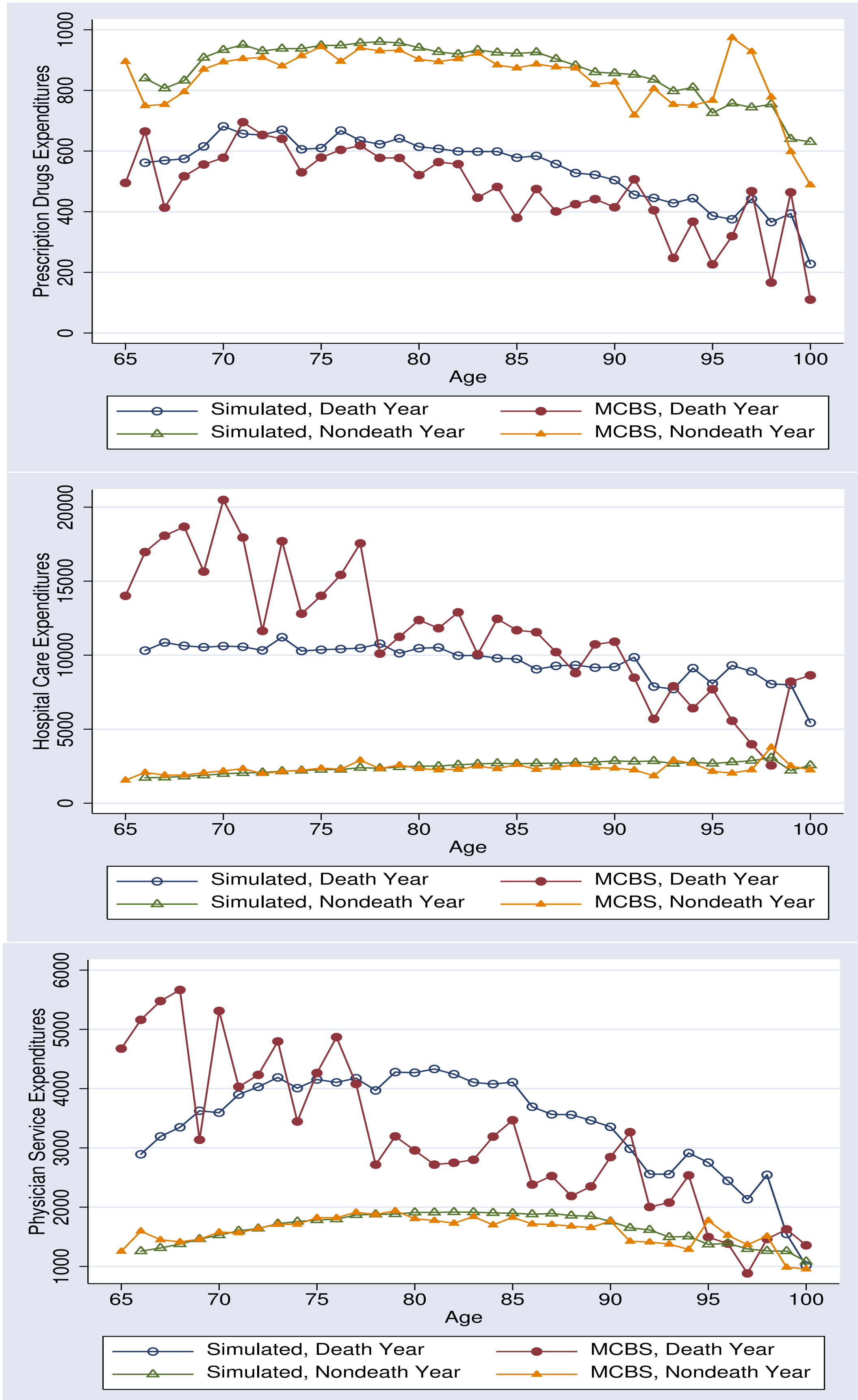

Figure 5: Actual and Simulated Expenditures, by Age and Death

Table 1: Empirical Distribution of Sample Participation in MCBS, 1992-2001

Years Followed	Number of individuals	Percent of sample
At least 2 years	25,935	100
At least 3 years	19,913	77
At least 4 years	3,574	13
More than 4 years	1,031	4
Exactly 2 years	6,022	23
Exactly 3 years	16,366	63
Exactly 4 years	2,516	10
More than 4 years	1,031	4
1992	6,470	8.5
1993	7,860	10.3
1994	8,675	11.4
1995	7,850	10.3
1996	7,480	9.8
1997	7,484	9.8
1998	7,227	9.4
1999	8,470	11.1
2000	8,954	11.7
2001	5,891	7.7
Number of unique individuals		25,935
Number of person-year observations		76,361

Table 2: Health Stock and Health Shocks

Observed One-Year Health Stock Transitions	Proportion[a]	Functional Status in year $t+1$ (H_{t+1}): No Disability	Moderately Disabled	Severely Disabled	Die
Functional Status in year t (H_t)					
No Disability (No ADL or IADL)	0.59	0.81	0.15	0.02	0.02
Moderately Disabled (IADL or up to 2 ADLs)	0.28	0.26	0.57	0.11	0.06
Severely Disabled (3 or more ADLs)	0.10	0.06	0.24	0.56	0.14
Dead	0.03	0.00	0.00	0.00	1.00

Probability of Health Shocks (Conditional on Existing Chronic Conditions)[b]	%	Health Shock During Year t (S_t^k): Heart/Stroke	Respiratory	Cancer
Chronic Condition entering year t (C_t^k)				
Heart/Stroke (ICD-9 390-439)	0.48	0.38	0.06	0.06
Respiratory (ICD-9 480-496)	0.15	0.32	0.20	0.07
Cancer (ICD-9 140-205)	0.20	0.27	0.18	0.06
Diabetes (ICD-9 250)	0.19	0.33	0.05	0.06
None	0.28	0.01	0.05	0.08

Note:
[a] Proportion is measured over all person-year observations in the sample.
[b] A person may have multiple chronic conditions or shocks.

Table 3: Description of Endogenous Variables[a]

Notation	Variable Name	Specification	Percent[b]	
I_t	Supplemental Insurance Plan in t	multinomial		
	Medicare Only (no supplement)	logit	8.05	
	Medicaid		11.96	
	Private Insurance		64.43	
	Medicare HMO alternative		15.56	
J_t	Prescription Drug Coverage in t conditional on Private or HMO plan	logit	62.99	
S_t	Health Shock in t			
	Heart/Stroke (ICD-9 390-496)	logit	24.47	
	Respiratory (ICD-9 480-496)	logit	4.79	
	Cancer (ICD-9 140-209)	logit	5.70	
$A_t > 0$	Any Hospitalization in t	logit	20.82	
$B_t > 0$	Any Physician Service Utilization in t	logit	83.79	
$D_t > 0$	Any Prescription Drug Utilization in t	logit	89.58	
$A_t \vert A_t > 0$	Hospital Expenditures in t	OLS	13057.64	(16900.38)
$B_t \vert B_t > 0$	Physician Service Expenditures in t	OLS	2013.00	(3359.87)
$D_t \vert D_t > 0$	Prescription Drug Expenditures in t	OLS	980.12	(1159.48)
H_{t+1}	Health Stock entering $t+1$ (at end of t)	multinomial		
	No Disability (No ADL or IADLs)	logit	57.74	
	Moderate Disability (IADL or < 3 ADLs)		28.05	
	Severe Disability (3 or more ADLs)		9.62	
	Dead		4.59	
C_t	Existing Chronic Conditions up to t			
	$C_{t+1} = C_t + S_t, t = 1, \ldots, T$			
	$C_1 = C_0$ where C_0 includes shocks at period $t = 0$[c]			
C_0	Heart/Stroke	logit	46.68	
	Respiratory	logit	15.02	
	Cancer	logit	19.26	
	Diabetes	logit	19.73	

Note:

[a] The statistics describe the distribution of dependent variables in the set of jointly estimated equations. These variables also serve as endogenous right-hand side variables.

[b] Means (in year 2001 dollars) are reported for expenditures. Standard deviations are in parentheses.

[c] The equations for C_0 are estimated in the first period only.
Statistics for additional initial condition equations are in Appendix Table A1.

Table 4: Description of Exogenous Variables

Variable Name	Mean	Standard Deviation
Non Time-Varying Individual Characteristics		
Education (range: 0-18 years)	6.72	2.67
Male (omitted: female)	0.42	0.49
Race (omitted: white)		
Black	0.09	0.29
Hispanic	0.02	0.13
Other Non-White	0.01	0.10
Veteran	0.23	0.42
Birth Decade (0 ≡ 1900)	1.63	0.81
Initial Height (range: 36-88 inches)	65.67	3.99
Time-Varying Individual Characteristics		
Age (range: 65-106 years)	75.67	7.11
Rural Resident (omitted: urban)	0.27	0.45
Marital Status (omitted: married)		
Widowed	0.38	0.49
Divorced, Separated, or Single	0.06	0.24
Annual Income (000's of year 2000 $)	26.58	57.49
Time-Varying Supply-Side Characteristics		
Medicare AAPCC Part A rate[a]	350.07	230.75
Medicare AAPCC Part B rate	226.56	140.53
Average Prescription Drugs Retail Price[b]	41.01	5.49
Reside within 100 miles of Canada/Mexico border[c]	0.17	0.37
# of Physicians per capita	18.01	14.26
# of Hospitals per capita	0.18	0.18
# of Hospitals beds per capita	30.52	22.12
% of HMO enrollees[d]	18.91	14.14
Median Air Quality Index[e]	34.79	11.04

Note:

[a] The projected average county-level fee-for-service spending for the coming year is used to set Medicare reimbursement rates, or adjusted average per capita cost (AAPCC) rates. These values and # of physicians, hospitals and beds per capita per county are from the Area Resourse Files.

[b] Drug prices were calculated as the total value of drug cost divided by total number of drugs sold in a particular state and year.

[c] Distance to the border was calculating using zip code centroids and North America Equidistant Conic map projections.

[d] We thank Lawrence Baker for measures of HMO penetration per county.

[e] The median Air Quality Index is reported for counties by the Environmental Protection Agency. Higher values indicate worse air quality.

Table 5a: Parameter Estimates for Selected Variables Explaining Prescription Drug Expenditures

Selected Variables	Any Prescription Drug Expenditures: Single Equation Without Unobserved Heterogeneity			Any Prescription Drug Expenditures: Multiple Equations With Unobserved Heterogeneity			Prescription Drug Expenditures, if Any: Single Equation Without Unobserved Heterogeneity			Prescription Drug Expenditures, if Any: Multiple Equations With Unobserved Heterogeneity		
Supplemental insurance												
Medicaid	0.430	(0.082)	**	0.329	(0.091)	**	0.209	(0.026)	**	0.194	(0.027)	**
Private without Rx coverage	0.322	(0.067)	**	0.349	(0.090)	**	0.094	(0.023)	**	0.024	(0.027)	
Private with Rx coverage	0.377	(0.066)	**	0.485	(0.123)	**	0.354	(0.023)	**	0.230	(0.033)	**
HMO without Rx coverage	0.348	(0.122)	**	0.425	(0.134)	**	0.060	(0.041)		0.086	(0.042)	**
HMO with Rx coverage	0.710	(0.078)	**	0.843	(0.087)	**	0.121	(0.026)	**	0.142	(0.027)	**
Health stock entering year t												
Moderately Disabled	0.218	(0.049)	**	0.260	(0.053)	**	0.272	(0.013)	**	0.277	(0.013)	**
Severely Disabled	0.091	(0.081)		0.127	(0.087)		0.307	(0.019)	**	0.318	(0.020)	**
Health Shocks during year t												
Heart/Stroke	1.092	(0.069)	**	0.774	(0.073)	**	0.262	(0.013)	**	0.200	(0.013)	**
Respiratory	0.571	(0.141)	**	–0.162	(0.148)		0.139	(0.026)	**	–0.052	(0.027)	*
Cancer	0.324	(0.102)	**	–0.203	(0.110)	*	0.041	(0.023)	*	–0.070	(0.024)	**
Chronic conditions entering year t												
Heart/Stroke	0.630	(0.044)	**	0.707	(0.048)	**	0.355	(0.012)	**	0.377	(0.012)	**
Respiratory	0.327	(0.066)	**	0.457	(0.073)	**	0.228	(0.015)	**	0.267	(0.016)	**
Cancer	0.061	(0.053)		0.082	(0.057)		0.013	(0.014)		0.027	(0.014)	*
Diabetes	0.665	(0.064)	**	0.678	(0.069)	**	0.360	(0.013)	**	0.366	(0.013)	**
Lagged medical care												
Any prescription drugs	2.994	(0.040)	**	3.240	(0.047)	**	1.710	(0.026)	**	1.783	(0.026)	**
Any inpatient stay	–0.358	(0.061)	**	–0.394	(0.065)	**	0.058	(0.014)	**	0.054	(0.015)	**
Any physician services	0.561	(0.046)	**	0.611	(0.050)	**	0.197	(0.018)	**	0.190	(0.019)	**
Unobserved heterogeneity												
Loading ρ on permanent factor μ	—	—		0.089	(0.116)		—	—		–0.139	(0.028)	**
Loading ω on time-varying factor ν_t	—	—		2.517	(0.081)	**	—	—		0.877	(0.018)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 5b: Parameter Estimates for Selected Variables Explaining Hospital Expenditures

Selected Variables	Any Hospital Services Expenditures: Single Equation Without Unobserved Heterogeneity			Any Hospital Services Expenditures: Multiple Equations With Unobserved Heterogeneity			Hospital Services Expenditures, if Any: Single Equation Without Unobserved Heterogeneity			Hospital Services Expenditures, if Any: Multiple Equations With Unobserved Heterogeneity		
Supplemental insurance												
Medicaid	0.049	(0.059)		–0.152	(0.084)		0.029	(0.042)		-0.035	(0.042)	
Private without Rx coverage	0.065	(0.054)		0.046	(0.086)		0.034	(0.039)		–0.015	(0.044)	
Private with Rx coverage	0.012	(0.053)		0.130	(0.113)		0.049	(0.039)		0.024	(0.055)	
HMO without Rx coverage	0.143	(0.101)		0.249	(0.141)	*	–0.270	(0.075)	**	–0.128	(0.075)	*
HMO with Rx coverage	0.301	(0.062)	**	0.531	(0.087)	**	–0.278	(0.046)	**	–0.147	(0.046)	**
Health stock entering year t												
Moderately Disabled	0.323	(0.030)	**	0.480	(0.040)	**	0.032	(0.021)		0.099	(0.021)	**
Severely Disabled	0.649	(0.042)	**	0.963	(0.056)	**	0.066	(0.028)	**	0.198	(0.028)	**
Health Shocks during year t												
Heart/Stroke	1.959	(0.028)	**	2.264	(0.038)	**	0.185	(0.020)	**	0.329	(0.020)	**
Respiratory	1.633	(0.054)	**	0.594	(0.083)	**	0.161	(0.028)	**	–0.139	(0.031)	**
Cancer	1.283	(0.048)	**	0.877	(0.071)	**	0.245	(0.028)	**	0.197	(0.030)	**
Chronic conditions entering year t												
Heart/Stroke	–0.077	(0.029)	**	0.112	(0.037)	**	0.020	(0.021)		0.093	(0.020)	**
Respiratory	–0.060	(0.036)		0.289	(0.048)	**	0.002	(0.024)		0.148	(0.024)	**
Cancer	–0.017	(0.032)		0.158	(0.042)	**	–0.011	(0.022)		0.062	(0.022)	**
Diabetes	0.206	(0.031)	**	0.336	(0.041)	**	0.059	(0.021)	**	0.117	(0.021)	**
Lagged medical care												
Any prescription drugs	0.307	(0.054)	**	0.407	(0.068)	**	–0.014	(0.043)		0.050	(0.041)	
Any inpatient stay	0.674	(0.031)	**	0.891	(0.040)	**	0.116	(0.021)	**	0.211	(0.020)	**
Any physician services	–0.211	(0.045)	**	–0.277	(0.059)	**	–0.076	(0.035)	**	–0.100	(0.034)	**
Unobserved heterogeneity												
Loading ρ on permanent factor μ	—	—		0.121	(0.098)		—	—		–0.019	(0.045)	
Loading ω on time-varying factor ν_t	—	—		7.351	(0.110)	**	—	—		2.683	(0.055)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 5c: Parameter Estimates for Selected Variables Explaining Physician Service Expenditures

Selected Variables	Any Physician Services Expenditures						Physician Services Expenditures, if Any					
	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity			Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
Supplemental insurance												
Medicaid	0.530	(0.071)	**	0.533	(0.076)	**	0.340	(0.032)	**	0.220	(0.035)	**
Private without Rx coverage	0.928	(0.063)	**	0.738	(0.080)	**	0.271	(0.028)	**	0.210	(0.034)	**
Private with Rx coverage	0.763	(0.059)	**	0.369	(0.097)	**	0.276	(0.028)	**	0.231	(0.050)	**
HMO without Rx coverage	–0.723	(0.091)	**	–0.701	(0.097)	**	–0.383	(0.057)	**	–0.350	(0.058)	**
HMO with Rx coverage	–1.118	(0.061)	**	–1.151	(0.065)	**	–0.535	(0.036)	**	–0.484	(0.039)	**
Health stock entering year t												
Moderately Disabled	0.055	(0.041)		0.069	(0.043)		0.195	(0.016)	**	0.211	(0.016)	**
Severely Disabled	0.000	(0.067)		0.034	(0.070)		0.339	(0.024)	**	0.376	(0.024)	**
Health Shocks during year t												
Heart/Stroke	2.689	(0.102)	**	2.528	(0.096)	**	0.946	(0.016)	**	0.690	(0.015)	**
Respiratory	1.599	(0.189)	**	1.105	(0.192)	**	0.675	(0.031)	**	–0.158	(0.036)	**
Cancer	2.825	(0.243)	**	2.461	(0.256)	**	1.092	(0.028)	**	0.615	(0.033)	**
Chronic conditions entering year t												
Heart/Stroke	0.178	(0.036)	**	0.197	(0.038)	**	0.072	(0.015)	**	0.150	(0.014)	**
Respiratory	0.108	(0.051)	**	0.179	(0.054)	**	0.160	(0.019)	**	0.327	(0.019)	**
Cancer	0.061	(0.045)		0.069	(0.048)		0.118	(0.017)	**	0.177	(0.017)	**
Diabetes	0.204	(0.045)	**	0.219	(0.048)	**	0.254	(0.017)	**	0.257	(0.017)	**
Lagged medical care												
Any prescription drugs	0.758	(0.044)	**	0.742	(0.046)	**	0.487	(0.026)	**	0.412	(0.026)	**
Any inpatient stay	–0.083	(0.052)		–0.090	(0.054)		0.312	(0.018)	**	0.299	(0.017)	**
Any physician services	2.322	(0.036)	**	2.403	(0.039)	**	0.616	(0.029)	**	0.691	(0.028)	**
Unobserved heterogeneity												
Loading ρ on permanent factor μ	—	—		–0.504	(0.088)	**	—	—		–0.051	(0.045)	
Loading ω on time-varying factor ν_t	—	—		1.618	(0.078)	**	—	—		3.783	(0.027)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 6a: Parameter Estimates for Selected Variables Explaining Health Stock Transitions

Outcome: (relative to no functional limitation)	Die					
Selected Variables	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
Health stock entering year t						
Moderately Disabled	1.770	(0.191)	**	1.706	(0.206)	**
Severely Disabled	4.139	(0.297)	**	4.170	(0.339)	**
Health shock during year t						
Heart/Stroke	0.704	(0.064)	**	0.322	(0.070)	**
Respiratory	0.398	(0.092)	**	0.639	(0.099)	**
Cancer	1.178	(0.080)	**	1.046	(0.085)	**
Medical care utilization and expenditures						
Any prescription drugs	0.920	(0.207)	**	0.795	(0.218)	**
Prescription drug expenditures	–0.261	(0.041)	**	–0.190	(0.042)	**
Any inpatient stay	–1.588	(0.557)	**	–2.272	(0.542)	**
Hospital expenditures	0.452	(0.066)	**	0.738	(0.067)	**
Any physician services	–0.887	(0.276)	**	–2.937	(0.302)	**
Physician service expenditures	0.067	(0.046)		0.582	(0.054)	**
Interaction of beginning health stock and medical care						
Moderately disabled × Any prescription drugs	0.860	(0.312)	**	0.925	(0.330)	**
Moderately disabled × Prescription drug expenditures	–0.100	(0.046)	**	–0.106	(0.048)	**
Moderately disabled × Any inpatient stay	0.003	(0.847)		0.061	(0.808)	
Moderately disabled × Hospital expenditures	0.017	(0.093)		0.008	(0.089)	
Moderately disabled × Any physician service	0.184	(0.379)		0.050	(0.389)	
Moderately disabled × Physician service expenditures	–0.047	(0.051)		–0.044	(0.052)	
Severely disabled × Any prescription drugs	0.162	(0.481)		0.099	(0.541)	
Severely disabled × Prescription drug expenditures	–0.002	(0.068)		0.003	(0.073)	
Severely disabled × Any inpatient stay	0.580	(1.247)		0.323	(0.865)	
Severely disabled × Hospital expenditures	–0.105	(0.138)		–0.080	(0.097)	
Severely disabled × Any physician service	1.123	(0.521)	**	0.916	(0.608)	
Severely disabled × Physician service expenditures	–0.158	(0.071)	**	–0.167	(0.079)	**
Interaction of different types of medical care expenditures						
Hospital × Prescription drugs	–0.011	(0.003)	**	–0.013	(0.003)	**
Hospital × Physician services	0.007	(0.002)	**	–0.012	(0.003)	**
Physician services × Prescription drugs	–0.010	(0.004)	**	–0.017	(0.005)	**
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		0.410	(0.071)	**
Loading ω on time-varying factor ν_t	—	—		–3.558	(0.192)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 6b: Parameter Estimates for Selected Variables Explaining Health Stock Transitions

Outcome: (relative to no functional limitation)	Severely Disabled					
Selected Variables	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
Health stock entering year t						
Moderately Disabled	3.833	(0.354)	**	3.807	(0.343)	**
Severely Disabled	6.723	(0.407)	**	6.741	(0.421)	**
Health shock during year t						
Heart/Stroke	–0.003	(0.051)		–0.116	(0.054)	**
Respiratory	0.189	(0.083)	**	0.248	(0.087)	**
Cancer	–0.051	(0.086)		–0.093	(0.089)	
Medical care utilization and expenditures						
Any prescription drugs	–0.078	(0.415)		–0.192	(0.403)	
Prescription drug expenditures	0.265	(0.050)	**	0.296	(0.052)	**
Any inpatient stay	–1.707	(0.717)	**	–1.890	(0.600)	**
Hospital expenditures	0.273	(0.085)	**	0.343	(0.074)	**
Any physician services	–0.926	(0.328)	**	–1.529	(0.351)	**
Physician service expenditures	0.160	(0.052)	**	0.309	(0.058)	**
Interaction of beginning health stock and medical care						
Moderately disabled × Any prescription drugs	–0.665	(0.475)		–0.637	(0.469)	
Moderately disabled × Prescription drug expenditures	–0.014	(0.051)		–0.016	(0.053)	
Moderately disabled × Any inpatient stay	2.047	(0.927)	**	2.003	(0.772)	**
Moderately disabled × Hospital expenditures	–0.266	(0.102)	**	–0.262	(0.085)	**
Moderately disabled × Any physician service	0.124	(0.382)		0.075	(0.395)	
Moderately disabled × Physician service expenditures	–0.065	(0.049)		–0.064	(0.051)	
Severely disabled × Any prescription drugs	–0.946	(0.573)		–0.994	(0.613)	
Severely disabled × Prescription drug expenditures	0.068	(0.067)		0.073	(0.072)	
Severely disabled × Any inpatient stay	1.050	(1.263)		0.807	(0.800)	
Severely disabled × Hospital expenditures	–0.232	(0.140)		–0.204	(0.089)	**
Severely disabled × Any physician service	0.965	(0.495)	*	0.922	(0.577)	
Severely disabled × Physician service expenditures	–0.181	(0.065)	**	–0.190	(0.073)	**
Interaction of different types of medical care expenditures						
Hospital × Prescription drugs	–0.001	(0.004)		–0.001	(0.004)	
Hospital × Physician services	0.010	(0.002)	**	0.006	(0.003)	**
Physician services × Prescription drugs	0.000	(0.005)		–0.002	(0.005)	
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		0.439	(0.052)	**
Loading ω on time-varying factor ν_t	—	—		–1.068	(0.155)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 6c: Parameter Estimates for Selected Variables Explaining Health Stock Transitions

Outcome: (relative to no functional limitation)	Moderately Disabled					
Selected Variables	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
Health stock entering year t						
Moderately Disabled	2.503	(0.107)	**	2.479	(0.110)	**
Severely Disabled	2.747	(0.285)	**	2.765	(0.303)	**
Health shock during year t						
Heart/Stroke	0.010	(0.033)		–0.077	(0.035)	**
Respiratory	0.227	(0.060)	**	0.277	(0.062)	**
Cancer	0.052	(0.055)		0.014	(0.056)	
Medical care utilization and expenditures						
Any prescription drugs	–0.497	(0.114)	**	–0.575	(0.116)	**
Prescription drug expenditures	0.187	(0.019)	**	0.210	(0.020)	**
Any inpatient stay	–0.481	(0.352)		–0.662	(0.373)	*
Hospital expenditures	0.093	(0.044)	**	0.149	(0.047)	**
Any physician services	–0.559	(0.101)	**	–1.040	(0.124)	**
Physician service expenditures	0.113	(0.020)	**	0.229	(0.026)	**
Interaction of beginning health stock and medical care						
Moderately disabled × Any prescription drugs	–0.030	(0.176)		–0.011	(0.179)	
Moderately disabled × Prescription drug expenditures	–0.020	(0.023)		–0.021	(0.023)	
Moderately disabled × Any inpatient stay	0.703	(0.591)		0.712	(0.647)	
Moderately disabled × Hospital expenditures	–0.100	(0.066)		–0.100	(0.072)	
Moderately disabled × Any physician service	0.364	(0.153)	**	0.339	(0.156)	**
Moderately disabled × Physician service expenditures	–0.080	(0.021)	**	–0.081	(0.021)	**
Severely disabled × Any prescription drugs	–0.520	(0.449)		–0.570	(0.484)	
Severely disabled × Prescription drug expenditures	0.117	(0.057)	**	0.122	(0.061)	**
Severely disabled × Any inpatient stay	0.205	(1.165)		0.063	(0.864)	
Severely disabled × Hospital expenditures	–0.073	(0.129)		–0.056	(0.097)	
Severely disabled × Any physician service	0.904	(0.405)	**	0.896	(0.466)	*
Severely disabled × Physician service expenditures	–0.175	(0.053)	**	–0.185	(0.060)	**
Interaction of different types of medical care expenditures						
Hospital × Prescription drugs	0.004	(0.002)		0.003	(0.002)	
Hospital × Physician services	0.000	(0.001)		–0.003	(0.002)	*
Physician services × Prescription drugs	–0.002	(0.002)		–0.004	(0.002)	
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		0.318	(0.032)	**
Loading ω on time-varying factor ν_t	—	—		–0.804	(0.113)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 7: Parameter Estimates for Selected Variables Explaining Supplemental Insurance (relative to Medicare coverage only)

Selected Variables	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
<u>Outcome: Medicaid</u>						
Health stock entering year t						
Moderately Disabled	0.366	(0.051)	**	0.441	(0.057)	**
Severely Disabled	0.668	(0.071)	**	0.851	(0.082)	**
Chronic conditions entering year t						
Heart/Stroke	0.384	(0.046)	**	0.395	(0.053)	**
Respiratory	0.375	(0.059)	**	0.443	(0.069)	**
Cancer	0.042	(0.058)		0.054	(0.068)	
Diabetes	0.357	(0.053)	**	0.380	(0.061)	**
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		8.406	(0.349)	**
Loading ω on time-varying factor ν_t	—	—		0.978	(0.116)	**
<u>Outcome: Private</u>						
Health stock entering year t						
Moderately Disabled	–0.143	(0.042)	**	–0.127	(0.077)	
Severely Disabled	–0.307	(0.062)	**	–0.437	(0.120)	**
Chronic conditions entering year t						
Heart/Stroke	0.231	(0.037)	**	0.148	(0.075)	**
Respiratory	0.091	(0.050)	*	–0.025	(0.100)	
Cancer	0.199	(0.047)	**	0.062	(0.096)	
Diabetes	0.083	(0.045)	*	0.087	(0.092)	
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		–15.664	(0.268)	**
Loading ω on time-varying factor ν_t	—	—		0.485	(0.140)	**
<u>Outcome: HMO</u>						
Health stock entering year t						
Moderately Disabled	–0.151	(0.049)	**	–0.128	(0.054)	**
Severely Disabled	–0.408	(0.077)	**	–0.436	(0.084)	**
Chronic conditions entering year t						
Heart/Stroke	–0.113	(0.043)	**	–0.062	(0.048)	
Respiratory	0.061	(0.059)		0.056	(0.066)	
Cancer	0.062	(0.054)		0.040	(0.061)	
Diabetes	0.152	(0.053)	**	0.121	(0.057)	**
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		–1.881	(0.245)	**
Loading ω on time-varying factor ν_t	—	—		–0.387	(0.104)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 8: Parameter Estimates for Selected Variables Explaining Prescription Drug Coverage (conditional on private or HMO supplemental insurance)

Selected Variables	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
HMO coverage (relative to private)	1.196	(0.036)	**	6.073	(0.088)	**
Health stock entering year t						
Moderately Disabled	0.074	(0.027)	**	0.069	(0.029)	**
Severely Disabled	0.039	(0.043)		–0.086	(0.055)	
Chronic conditions entering year t						
Heart/Stroke	0.010	(0.023)		–0.039	(0.030)	
Respiratory	0.062	(0.032)	**	0.170	(0.043)	**
Cancer	–0.064	(0.027)	**	–0.216	(0.032)	**
Diabetes	0.003	(0.029)		0.169	(0.036)	**
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		–8.056	(0.108)	**
Loading ω on time-varying factor ν_t	—	—		–0.165	(0.096)	*

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level. Additional explanatory variables include individual demographic and economic information and relevant county/state-level supply-side variables.

Table 9: Parameter Estimates for Selected Variables Explaining Health Shocks

Selected Variables	Single Equation Without Unobserved Heterogeneity			Multiple Equations With Unobserved Heterogeneity		
Shock: Heart/Stroke						
Health stock entering year t						
Moderately Disabled	0.205	(0.026)	**	0.214	(0.026)	**
Severely Disabled	0.292	(0.037)	**	0.317	(0.038)	**
Chronic conditions entering year t						
Heart/Stroke	1.417	(0.024)	**	1.419	(0.025)	**
Respiratory	0.218	(0.029)	**	0.224	(0.030)	**
Cancer	0.039	(0.027)		0.025	(0.028)	
Diabetes	0.361	(0.026)	**	0.371	(0.027)	**
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		–0.384	(0.028)	**
Loading ω on time-varying factor ν_t	—	—		1.000	(—)	
Shock: Respiratory						
Health stock entering year t						
Moderately Disabled	0.410	(0.051)	**	0.434	(0.056)	**
Severely Disabled	0.521	(0.069)	**	0.590	(0.078)	**
Chronic conditions entering year t						
Heart/Stroke	0.445	(0.048)	**	0.519	(0.053)	**
Respiratory	2.314	(0.046)	**	2.592	(0.055)	**
Cancer	0.110	(0.052)	**	0.149	(0.057)	**
Diabetes	–0.033	(0.054)		0.003	(0.060)	
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		–0.190	(0.063)	**
Loading ω on time-varying factor ν_t	—	—		5.658	(0.266)	**
Shock: Cancer						
Health stock entering year t						
Moderately Disabled	0.190	(0.047)	**	0.208	(0.050)	**
Severely Disabled	–0.100	(0.075)		–0.053	(0.078)	
Chronic conditions entering year t						
Heart/Stroke	0.117	(0.042)	**	0.109	(0.045)	**
Respiratory	0.082	(0.052)		0.094	(0.055)	*
Cancer	2.157	(0.041)	**	2.202	(0.043)	**
Diabetes	0.085	(0.050)	*	0.119	(0.053)	**
Unobserved heterogeneity						
Loading ρ on permanent factor μ	—	—		–0.470	(0.055)	**
Loading ω on time-varying factor ν_t	—	—		2.716	(0.171)	**

Note:
Standard errors are in parentheses. **indicates joint significance at the 5% level; * 10% level.
Additional explanatory variables include individual demographic and economic information and county/state-level supply-side variables.
The factor loading on time-varying heterogeneity in the heart/stroke equation is normalized to one.

Table 10: Comparisons of Actual Observations and Model Predictions, by year

Year		1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	Average
Medical Care Expenditures												
Probability of Prescription Drug Use												
	MCBS	0.87	0.87	0.87	0.88	0.88	0.90	0.91	0.91	0.92	0.92	0.90
	Simulation	0.84	0.88	0.87	0.88	0.89	0.90	0.91	0.92	0.92	0.92	0.93
Prescription Drugs Exp, If Any												
	MCBS	846	711	754	781	828	896	1,023	1,142	1,283	1,435	969
	Simulation	—	716	788	812	863	936	1,014	1,199	1,364	1,553	1,012
Probability of Hospitalization												
	MCBS	0.17	0.19	0.20	0.19	0.19	0.20	0.19	0.20	0.20	0.22	0.20
	Simulation	0.13	0.18	0.19	0.18	0.19	0.17	0.17	0.19	0.19	0.22	0.18
Hospital Expenditures, If Any												
	MCBS	15,128	13,304	13,452	13,082	12,852	12,537	12,181	12,217	12,826	13,155	13,012
	Simulation	—	12,691	12,410	12,801	12,423	12,976	13,106	12,691	12,589	13,689	12,812
Probability of Physician Services												
	MCBS	0.94	0.86	0.86	0.87	0.87	0.87	0.86	0.76	0.77	0.79	0.84
	Simulation	0.93	0.89	0.87	0.87	0.86	0.84	0.81	0.79	0.77	0.80	0.84
Physician Service Expenditures, In Any												
	MCBS	2,615	1,845	1,941	1,642	2,000	2,037	2,085	1,957	2,093	2,337	2,039
	Simulation	—	1,860	1,828	1,855	1,967	2,016	2,200	2,340	2,372	2,389	2,070
Health Status												
Probability of Moderately Disabled												
	MCBS	0.31	0.30	0.30	0.29	0.29	0.29	0.29	0.28	0.28	0.30	0.29
	Simulation	0.32	0.25	0.25	0.26	0.27	0.25	0.26	0.28	0.28	0.27	0.27
Probability of Severely Disabled												
	MCBS	0.10	0.09	0.10	0.10	0.09	0.09	0.10	0.09	0.10	0.09	0.10
	Simulation	0.10	0.07	0.07	0.08	0.07	0.07	0.07	0.08	0.08	0.08	0.08
Probability of Death												
	MCBS	0	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.05	0.03
	Simulation	0	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04

Table 10: — continued

Year		**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**Average**
Supplemental Insurance Choice												
Medicaid												
	MCBS	0.13	0.11	0.12	0.12	0.12	0.11	0.11	0.12	0.11	0.13	0.12
	Simulation	0.10	0.08	0.08	0.08	0.08	0.07	0.11	0.09	0.09	0.09	0.08
Private												
	MCBS	0.68	0.68	0.68	0.66	0.65	0.64	0.63	0.61	0.60	0.61	0.64
	Simulation	0.71	0.71	0.70	0.69	0.68	0.66	0.64	0.64	0.64	0.64	0.67
HMO												
	MCBS	0.08	0.10	0.11	0.14	0.15	0.17	0.19	0.20	0.20	0.19	0.15
	Simulation	0.08	0.12	0.12	0.14	0.16	0.19	0.19	0.20	0.21	0.21	0.16
Rx benefit, If Private or HMO												
	MCBS	0.45	0.51	0.51	0.61	0.63	0.66	0.68	0.72	0.72	0.74	0.63
	Simulation	0.49	0.44	0.47	0.58	0.60	0.60	0.60	0.66	0.66	0.68	0.60
# of observations		6,470	7,860	8,675	7,850	7,480	7,484	7,227	8,470	8,954	5,891	76,361

Note: Observations in this table include only those observed *and* simulated to be alive in a particular year.
By construction, everyone in 1992 survives because individuals contribute a minimum of two years of data to estimation.

Table 11: Five-year Simulation of Medial Care Expenditures and Health Outcomes

	No Benefit	Medicaid Benefit	% △*	Private Benefit	% △*	HMO Benefit	% △*
Medical Care Expenditures (total over five years)							
With Unobserved Heterogeneity							
Prescription Drug Expenditures	5,311	6,942	**30.7**	7,195	**35.5**	6,337	**19.3**
Hospital Expenditures	11,432	10,599	**–7.3**	12,559	**9.9**	12,698	**11.1**
Physician Service Expenditures	7,170	9,623	**34.2**	9,638	**34.4**	3,810	**–46.9**
Total Medical Care Expenditures	23,913	27,164	**13.6**	29,392	**22.9**	22,845	**–4.5**
Without Unobserved Heterogeneity							
Prescription Drug Expenditures	4,310	5,838	**35.4**	6,810	**57.9**	4,997	**15.9**
Hospital Expenditures	12,226	13,296	**8.8**	13,277	**8.6**	11,785	**–3.6**
Physician Service Expenditures	5,263	8,195	**55.7**	7,882	**49.8**	2,544	**–51.7**
Total Medical Care Expenditures	21,799	27,329	**25.4**	27,969	**28.3**	19,326	**–11.3**
Health Outcomes (at end of five years)							
With Unobserved Heterogeneity							
Survival	80.76	82.59	**1.8**	81.47	**0.8**	80.87	**0.1**
Survivors without Disabilities	58.40	57.54	**–1.5**	56.65	**–1.8**	57.97	**–0.4**
Moderately Disabled Survivors	29.79	30.40	**1.2**	30.82	**1.2**	28.85	**0.4**
Severely Disabled Survivors	11.81	12.06	**0.3**	12.44	**0.6**	11.09	**0.0**
Without Unobserved Heterogeneity							
Survival	78.49	81.05	**2.6**	82.14	**3.7**	77.53	**–0.9**
Survivors without Disabilities	59.36	55.92	**–3.5**	55.11	**–4.3**	58.52	**–0.9**
Moderately Disabled Survivors	29.31	30.97	**1.7**	31.45	**2.1**	29.98	**0.7**
Severely Disabled Survivors	11.32	13.12	**1.8**	13.44	**2.1**	11.50	**0.2**

Note: * % △ refers to percentage change when the outcome is in levels (expenditures) and percentage point change when the outcome is a percent (health).
We report changes in behaviors from simulations of no drug coverage to the observed benefit structure (combinations of no supplemental coverage, Medicaid coverage, and private coverage of drugs), to a Medicaid-like benefit, and to a private insurance benefit, respectively.

Table 12: Total (five-year) Expenditures of Sole Survivors vs. Marginal Survivors with Different Types of Prescription Drug Coverage

	Medicaid		Private		HMO	
	Marginal	Sole	Marginal	Sole	Marginal	Sole
Initial Condition						
Age	77.85	73.83	77.89	73.82	77.29	73.75
Male	0.48	0.40	0.44	0.40	0.47	0.40
Income:	9.53	9.81	9.61	9.81	9.65	9.81
Height:	65.69	65.69	65.66	65.69	65.90	65.68
Moderately Disabled	0.37	0.26	0.36	0.26	0.34	0.30
Severely Disabled	0.18	0.07	0.18	0.06	0.13	0.11
Cancer	0.23	0.18	0.23	0.18	0.22	0.25
Heart Diseases and Stroke	0.51	0.44	0.54	0.44	0.49	0.43
Respiratory System Diseases	0.16	0.14	0.18	0.14	0.17	0.14
Diabetes	0.20	0.19	0.21	0.19	0.19	0.19
Total Medical Care Expenditures						
Prescription Drug Expenditures						
Without Benefit	2,288	5,926	2,490	5,892	2,698	5,903
With Benefit	6,881	7,615	8,063	7,919	6,967	7,004
%Δ	**200.7**	**28.5**	**223.8**	**34.4**	**158.2**	**18.7**
Hospital Expenditures						
Without Benefit	15,035	10,428	14,689	10,524	15,626	10,515
With Benefit	18,063	9,536	22,010	11,487	20,982	11,811
%Δ	**20.1**	**–8.6**	**49.9**	**9.2**	**34.3**	**12.3**
Physician Service Expenditures						
Without Benefit	5,464	7,505	5,804	7,444	6,815	7,427
With Benefit	12,944	10,018	13,692	10,050	5,962	3,846
%Δ	**136.9**	**33.5**	**135.9**	**35.0**	**–12.5**	**–48.2**
Total Medical Care Expenditures						
Without Benefit	22,788	23,859	22,982	23,860	25,139	23,845
With Benefit	37,888	27,169	43,766	29,456	33,911	22,662
%Δ	**66.3**	**13.9**	**90.4**	**23.5**	**34.9**	**–5.0**

Note: * % △ refers to percentage change when the outcome is in levels (expenditures) and percentage point change when the outcome is a percent (health).

Table 13: Total (five-year) Expenditures by Health Transition among Sole Survivors with Different Types of Prescription Drug Coverage

	Medicaid			Private			HMO		
	Without Benefit	With Benefit	% △*	Without Benefit	With Benefit	% △*	Without Benefit	With Benefit	% △*
Distribution									
Improved	16.00	16.20	**0.20**	16.91	16.21	**–0.70**	16.91	16.89	**–0.02**
Maintained	56.35	56.70	**0.35**	57.03	57.31	**0.28**	57.10	57.06	**–0.04**
Deteriorated	26.04	26.02	**–0.02**	26.05	26.48	**0.43**	25.99	26.05	**0.06**
Prescription Drug Expenditures									
Improved	6,476	8,225	**27.0**	6,493	8,575	**32.1**	6,516	7,605	**16.7**
Maintained	5,316	6,932	**30.4**	5,323	7,221	**35.7**	5,331	6,369	**19.5**
Deteriorated	6,993	8,757	**25.2**	6,996	9,144	**30.7**	7,038	8,266	**17.5**
Hospital Expenditures									
Improved	11,492	10,495	**–8.7**	11,533	12,528	**8.6**	11,628	12,889	**10.8**
Maintained	8,676	7,890	**–9.1**	8,685	9,482	**9.2**	8,696	10,116	**16.3**
Deteriorated	13,596	12,472	**–8.3**	13,591	14,654	**7.8**	13,628	14,727	**8.1**
Physician Service Expenditures									
Improved	7,593	10,625	**39.9**	7,953	10,730	**34.9**	8,019	4,195	**–47.7**
Maintained	6,718	9,053	**34.8**	6,711	9,054	**34.9**	6,696	3,432	**–48.8**
Deteriorated	8,962	11,673	**30.3**	8,944	11,820	**32.2**	8,969	4,771	**–45.8**
Total Medical Care Expenditures									
Improved	25,561	29,345	**14.8**	25,979	31,833	**22.5**	26,163	24,689	**–5.6**
Maintained	20,710	23,875	**15.3**	20,719	25,757	**24.3**	20,723	19,917	**–3.9**
Deteriorated	29,551	32,700	**10.7**	29,531	35,618	**20.1**	29,635	27,764	**–6.3**

Note: * % △ refers to percentage change when the outcome is in levels (expenditures) and percentage point change when the outcome is a percent (health).

Table 14: One-year Simulation of Medical Care Expenditures and Health Outcomes

	No Benefit	Medicaid Benefit	% △*	Private Benefit	% △*	HMO Benefit	% △*
Medical Care Expenditures (total for one-year)							
With Unobserved Heterogeneity							
Prescription Drug Expenditures	873	1,157	**32.5**	1,188	**26.5**	1,047	**19.9**
Hospital Expenditures	2,157	1,965	**–8.9**	2,351	**8.3**	2,337	**8.3**
Physician Service Expenditures	1,277	1,771	**38.7**	1,752	**27.1**	631	**–50.6**
Total Medical Care Expenditures	4,307	4,893	**13.6**	5,291	**18.6**	4,015	**–6.8**
Without Unobserved Heterogeneity							
Prescription Drug Expenditures	709	964	**36.0**	1,122	**58.3**	835	**17.8**
Hospital Expenditures	2,372	2,510	**5.8**	2,482	**4.6**	2,243	**–5.4**
Physician Service Expenditures	918	1,460	**59.0**	1,393	**51.7**	419	**–54.4**
Total Medical Care Expenditures	3,999	4,934	**23.4**	4,999	**25.0**	3,497	**–10.2**
Health Outcomes (at end of one year)							
With Unobserved Heterogeneity							
Survival	96.13	96.68	**0.55**	96.44	**0.31**	96.23	**0.10**
Survivors without Disabilities	61.41	60.26	**–1.62**	60.16	**–1.58**	61.38	**–0.03**
Moderately Disabled Survivors	26.93	27.92	**0.99**	27.88	**0.95**	27.15	**0.00**
Severely Disabled Survivors	8.52	9.15	**0.63**	9.15	**0.63**	8.55	**0.03**
Without Unobserved Heterogeneity							
Survival	95.28	96.12	**0.84**	96.41	**1.13**	95.19	**–0.08**
Survivors without Disabilities	64.74	63.13	**–1.61**	62.79	**–1.95**	64.15	**–0.59**
Moderately Disabled Survivors	26.91	27.78	**0.86**	28.00	**1.09**	27.38	**0.47**
Severely Disabled Survivors	8.35	9.09	**0.74**	9.21	**0.86**	8.47	**0.12**

Note: * % △ refers to percentage change when the outcome is in levels (expenditures) and percentage point change when the outcome is a percent (health).
We report changes in behaviors from simulations of no drug coverage to the observed benefit structure (combinations of no supplemental coverage, Medicaid coverage, and private coverage of drugs), to a Medicaid-like benefit, and to a private insurance benefit, respectively.

Appendix

An individual n in our sample data is followed from two to five years. We model her behavior in each annual period t, $t = 1, \ldots, T_n$. Our dynamic equations at $t = 1$ depend on values of explanatory variables at $t = 0$, which represents the first year an individual is observed in our data. We recognize that these initial values are likely to be functions of the same individual unobservables that influence behavior in subsequent periods. That is, they are functions of the permanent individual heterogeneity denoted μ. We also recognize that these values cannot be estimated using the same health production, insurance, or demand functions specified in Section 3. Hence, we explain variations in these initial observations using reduced form equations and allow them to be correlated with the permanent heterogeneity components that affect subsequent outcomes. These initial equations are estimated jointly with the set of dynamic equations specified in Section 3.2. We use λ^r to indicate estimated parameters in the initial reduced form equation r.

We include four equations explaining the initially observed (in our sample) existence of four chronic conditions, k: heart problems, respiratory problems, cancer, and diabetes.

$$\begin{aligned} \ln\left[\frac{\Pr(C_0^k = 1)}{\Pr(C_0^k = 0)}\right] &= \lambda_0^{1k} + \lambda_1^{1k} X_t + \lambda_2^{1k} Z_0^H + \lambda_2^{1k} R_0 + \rho^{1k}\mu \\ & \quad k = 1, 2, 3, \text{ or } 4. \end{aligned}$$

The probability of initially observed supplemental health insurance is a multinomial logit where

$$\begin{aligned} \ln\left[\frac{\Pr(I_0 = i)}{\Pr(I_0 = 0)}\right] &= \lambda_{i0}^2 + \lambda_{i1}^2 X_0 + \lambda_{i2}^2 Z_0^I + \lambda_{i3}^2 R_0 + \rho_i^2 \mu \\ & \quad i = 1, 2, \text{ or } 3. \end{aligned}$$

An indicator of drug benefits ($J_0 = 1$) is modeled as a logit outcome for individuals with private health insurance or Medicare managed care where

$$\ln\left[\frac{\Pr(J_0 = 1 | I_0 = 3 \text{ or } 4)}{\Pr(J_0 = 0 | I_0 = 3 \text{ or } 4)}\right] = \lambda_0^3 + \lambda_1^3 X_0 + \lambda_2^3 Z_0^I + \lambda_3^3 R_0 + \rho^3 \mu \ .$$

We must model initial medical care utilization as these choices may affect medical care decisions in the subsequent period. The probability of any hospital, physician, or drug expenditures, q, is

$$\begin{aligned} \ln\left[\frac{\Pr(q_0 > 0)}{\Pr(q_0 = 0)}\right] &= \lambda_0^{4q} + \lambda_1^{4q} X_0 + \lambda_2^{4q} Z_0^P + \lambda_3^{4q} R_0 + \rho_1^{4q} \mu \\ & \quad q = A, B, \text{ or } D. \end{aligned}$$

There is no need to model expenditures conditional on any in the initial period. The level of expenditures do explain health production at the end of each period, but these expenditures are modeled each period. Finally, general health stock entering period 1 is a multinomial logit with the outcomes no disability (no ADLs or IADLs), moderate disability (at least one IADL limitation and up to two ADL limitations), and severe disability (more than two ADL limitations) where

$$\ln\left[\frac{\Pr(H_1 = h)}{\Pr(H_1 = 0)}\right] = \lambda^5_{h0} + \lambda^5_{h1}X_0 + \lambda^5_{h2}Z^H_0 + \lambda^5_{h3}C_0 + \lambda^5_{h4}R_0 + \rho^5_h\mu$$
$$h = 1 \text{ and } 2.$$

All equations contain exogenous variables (R_0) that are excluded from the subsequent dynamic equations in $t = 1, \ldots, T$. The supply-side variables (Z_0) affect outcomes where appropriate. The permanent individual unobserved heterogeneity captured by μ affects each of these initial outcomes allowing them to be correlated with subsequent modeled outcomes.

We treat the unobserved heterogeneity (μ and ν_t) as discrete random effects and integrate them out of the model (see Heckman and Singer (1983) and Mroz (1999) for analyses comparing this procedure and others). This method of allowing correlation in unobservables across multiple equations without imposing a distributional form has been used in a wide variety of empirical applications including health (Goldman, 1995; Cutler, 1995; Blau and Gilleskie, 2001; Mays and Norton, 2000; Mello, Stearns, and Norton, 2002), welfare participation (Hoynes, 1996), child care (Blau and Hagy, 1998; Hu, 1999), disability insurance (Kreider and Riphahn, 2000), and program evaluation (Angeles et al., 1998). Different from the fixed effect or the general random effect approach, the discrete random effect approach assumes error terms in the correlated equations have discrete distributions of several mass points of support μ_m and an accompanying probability weight θ_m , $m = 1, \ldots, M$, where M is determined empirically. Analogously, the points of support of the time-varying heterogeneity, $\nu_{\ell t}$, and the probability weights, ψ_ℓ , $\ell = 1, \ldots, L$, are estimated (with the appropriate normalizations for identification).[22] This approach models the common heterogeneity that affects health insurance, health expenditures, health outcomes, and initial conditions. Unlike a fixed effect approach, this approach does not require estimation of $N - 1$ additional parameters, where N is the total number of individuals in the sample. Additionally, there is no distributional assumption imposed on the error terms μ and ν_t and, hence, the method minimizes possible estimation bias from the stronger assumption of a specific error distribution, such as joint normality, which is commonly assumed in models of joint behavior (Mroz, 1999). The likelihood function is

[22] We do not estimate M and L non-parametrically. Rather, we estimate the model by maximum likelihood for a fixed M and L. We then increase the values of M and L independently to obtain the best fit based on comparisons of the log likelihood values.

$$
\begin{aligned}
\mathcal{L}(\Theta) \quad = \quad & \prod_{n=1}^{N}\Bigg\{\sum_{m=1}^{M}\theta_m\prod_{k=1}^{4}(\Pr(C_0^k=0|\mu_m)^{\mathbf{1}(C_{n0}^k=0)}\cdot\Pr(C_0^k=1|\mu_m)^{\mathbf{1}(C_{n0}^k=1)}) \qquad \text{(A.1)}\\
& \cdot\prod_{i=0}^{3}\Pr(I_0=i|\mu_m)^{\mathbf{1}(I_{n0}=i)}(\prod_{j=0}^{1}\Pr(J_0=j|\mu_m)^{\mathbf{1}(J_{n0}=j)})^{\mathbf{1}(I_{n0}=2\text{ or }3)}\\
& \cdot\Pr(A_0=0|\mu_m)^{\mathbf{1}(A_{n0}=0)}[(1-\Pr(A_0>0|\mu_m)]^{\mathbf{1}(A_{n0}>0)}\\
& \cdot\Pr(B_0=0|\mu_m)^{\mathbf{1}(B_{n0}=0)}[(1-\Pr(B_0>0|\mu_m)]^{\mathbf{1}(B_{n0}>0)}\\
& \cdot\Pr(D_0=0|\mu_m)^{\mathbf{1}(D_{n0}=0)}[(1-\Pr(D_0>0|\mu_m)]^{\mathbf{1}(D_{n0}>0)}\\
& \cdot\prod_{h=0}^{2}\Pr(H_1=h|\mu_m)^{\mathbf{1}(H_{n1}=h)}\\
& \prod_{t=1}^{T_n}\Bigg[\sum_{\ell=1}^{L}\psi_\ell\prod_{i=0}^{3}\Pr(I_t=i|\mu_m,\nu_{\ell t})^{\mathbf{1}(I_{nt}=i)}(\prod_{j=0}^{1}\Pr(J_t=j|\mu_m,\nu_{\ell t})^{\mathbf{1}(J_{nt}=j)})^{\mathbf{1}(I_{nt}=2\text{ or }3)}\\
& \qquad\cdot\prod_{k=1}^{3}(\Pr(S_t^k=0|\mu_m,\nu_{\ell t})^{\mathbf{1}(S_{nt}^k=0)}\Pr(S_t^k=1|\mu_m,\nu_{\ell t})^{\mathbf{1}(S_{nt}^k=1)})\\
& \qquad\cdot\Pr(A_t=0|\mu_m,\nu_{\ell t})^{\mathbf{1}(A_{nt}=0)}\cdot[(1-\Pr(A_t=0)|\mu_m,\nu_{\ell t})\cdot\phi_A(\cdot|\mu_m,\nu_{\ell t})]^{\mathbf{1}(A_{nt}>0)}\\
& \qquad\cdot\Pr(B_t=0|\mu_m,\nu_{\ell t})^{\mathbf{1}(B_{nt}=0)}\cdot[(1-\Pr(B_t=0)|\mu_m,\nu_{\ell t})\cdot\phi_B(\cdot|\mu_m,\nu_{\ell t})]^{\mathbf{1}(B_{nt}>0)}\\
& \qquad\cdot\Pr(D_t=0|\mu_m,\nu_{\ell t})^{\mathbf{1}(D_{nt}=0)}\cdot[(1-\Pr(D_t=0)|\mu_m,\nu_{\ell t})\cdot\phi_D(\cdot|\mu_m,\nu_{\ell t})]^{\mathbf{1}(D_{nt}>0)}\\
& \qquad\cdot\prod_{h=0}^{3}\Pr(H_{t+1}=h|\mu_m,\nu_{\ell t})^{\mathbf{1}(H_{nt+1}=h)}\Bigg]\Bigg\}.
\end{aligned}
$$

Density functions for expenditures are denoted by $\phi_q(\cdot), q = A, B,$ and D and Θ represents the vector of all estimated parameters including those that capture the discrete distribution of the unobserved heterogeneity.

Table A1: Description of Dependent Variables in Initial Condition Equations

Notation	Variable Name	Specification	Percent
I_0	Supplemental Insurance Plan in $t = 0$	multinomial	
	Medicare Only (no supplement)	logit	8.63
	Medicaid		11.53
	Private Insurance		64.90
	Medicare HMO alternative		14.94
J_0	Prescription Drug Coverage in $t = 0$	logit	61.83
	conditional on Private or HMO plan		
$A_0 > 0$	Any Hospitalization in $t = 0$	logit	17.33
$B_0 > 0$	Any Physician Service Utilization in $t = 0$	logit	84.91
$D_0 > 0$	Any Prescription Drug Utilization in $t = 0$	logit	89.22
H_1	Health Stock entering $t = 1$ (at end of $t = 0$)	multinomial	
	No Disability (No ADL or IADLs)	logit	62.46
	Moderately Disabled (IADL or up to 2 ADLs)		28.31
	Severely Disabled (3 or more ADLs)		9.23
C_0	Existing Chronic Conditions up to and including $t = 0$		
	Heart/Stroke	logit	46.68
	Respiratory	logit	15.02
	Cancer	logit	19.26
	Diabetes	logit	19.73

Table A2: Parameter Estimates Explaining Initial Chronic Conditions

	Heart/Stroke	Respiratory	Cancer	Diabetes
Age	0.066**	0.009	0.048**	0.017**
	(0.007)	(0.009)	(0.008)	(0.009)
Age Squared	–0.095**	–0.094**	–0.102**	–0.191**
	(0.023)	(0.035)	(0.029)	(0.032)
Male	0.044	0.075	–0.169**	0.125**
	(0.040)	(0.055)	(0.050)	(0.051)
Education	–0.024**	–0.040**	0.028**	–0.032**
	(0.006)	(0.008)	(0.007)	(0.007)
Race: Black	0.107**	–0.194**	–0.128**	0.603**
	(0.045)	(0.063)	(0.058)	(0.051)
Race: Hispanic	–0.232**	–0.193	–0.252*	0.519**
	(0.100)	(0.136)	(0.139)	(0.108)
Race: Other nonwhite	–0.252**	–0.096	–0.319*	0.279*
	(0.127)	(0.174)	(0.180)	(0.145)
Marital Status: Widowed	0.071**	0.035	0.049	0.030
	(0.032)	(0.045)	(0.040)	(0.041)
Marital Status: Separated, Divorced, Single	0.075	0.153**	0.177**	–0.168**
	(0.053)	(0.068)	(0.065)	(0.066)
Ln(Income)	0.125**	0.119	–0.075	0.242**
	(0.059)	(0.077)	(0.072)	(0.084)
Ln(Income) Squared	–0.116**	–0.141**	0.063	–0.180**
	(0.034)	(0.046)	(0.041)	(0.048)
Rural	0.206**	0.172**	–0.027	0.031
	(0.029)	(0.039)	(0.036)	(0.036)
Birth Cohort	0.090**	–0.052	0.031	–0.066
	(0.033)	(0.046)	(0.042)	(0.042)
Height	0.018**	–0.011*	0.024**	0.015**
	(0.005)	(0.007)	(0.006)	(0.006)
Smoke Ever	0.191**	0.783**	0.130**	–0.085**
	(0.028)	(0.042)	(0.035)	(0.036)
Loading ρ on permanent factor μ	–0.119**	0.027	–0.141**	1.000
	(0.033)	(0.045)	(0.040)	(.—)

Note:
Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level.
The results are from four logit regressions (estimated jointly with the other equations).
The factor loading on permanent heterogeneity in the diabetes equation is normalized to one.

Table A3: Parameter Estimates Explaining Initial Supplemental Insurance

	Medicaid	Private	HMO	Drug Coverage if private or HMO
HMO Supplemental Insurance	—	—	—	5.661**
	—	—	—	(0.101)
Chronic Condition: Heart/Stroke	0.486**	0.072	–0.164**	–0.048
	(0.067)	(0.082)	(0.064)	(0.037)
Chronic Condition: Respiratory	0.632**	0.024	0.136	0.094*
	(0.089)	(0.113)	(0.088)	(0.055)
Chronic Condition: Cancer	0.053	0.205*	0.022	–0.174**
	(0.088)	(0.107)	(0.084)	(0.042)
Chronic Condition: Diabetes	0.409**	0.100	0.079	0.214**
	(0.078)	(0.101)	(0.078)	(0.047)
Age	0.001	0.071**	0.045**	–0.035**
	(0.017)**	(0.021)	(0.017)	(0.008)
Age Squared	–0.004	–0.183**	–0.177**	—
	(0.052)**	(0.068)	(0.056)	—
Male	0.008	–0.977**	–0.311**	–0.075
	(0.103)	(0.131)	(0.100)	(0.077)
Education	–0.112**	0.106**	0.064**	0.044**
	(0.014)	(0.017)	(0.015)	(0.009)
Race: Black	1.404**	–5.911**	–0.953**	–2.027**
	(0.105)	(0.157)	(0.110)	(0.091)
Race: Hispanic	3.098**	–7.133**	–0.727**	–2.734**
	(0.238)	(0.377)	(0.246)	(0.229)
Race: Other nonwhite	1.342**	–5.280**	–0.776**	–2.163**
	(0.260)	(0.355)	(0.261)	(0.235)
Marital Status: Widowed	0.158*	–0.212**	–0.089	–0.049
	(0.081)	(0.098)	(0.078)	(0.044)
Marital Status: Separated, Divorced, Single	0.512**	–1.203**	–0.308**	–0.059
	(0.113)	(0.156)	(0.111)	(0.107)
Ln(Income)	1.473**	–0.981**	–0.496**	–0.204
	(0.174)	(0.141)	(0.118)	(0.124)
Ln(Income) Squared	–1.259**	0.999**	0.633**	0.235**
	(0.110)	(0.091)	(0.076)	(0.069)
Rural	0.100	–0.358**	–0.994**	–0.182**
	(0.085)	(0.106)	(0.093)	(0.053)
Birth Cohort	0.171	–0.171	0.083	–0.019
	(0.112)	(0.130)	(0.104)	(0.075)
Veteran	–1.081**	–0.061	–0.325**	0.172**
	(0.113)**	(0.118)	(0.091)	(0.063)
Initial Height	–0.054**	0.044**	0.002	–0.005
	(0.011)**	(0.013)	(0.010)	(0.009)
HMO Penetration	3.960**	–2.018**	5.520**	2.697**
	(0.317)	(0.377)	(0.289)	(0.230)
Calendar Year	–0.059**	–0.049**	0.128**	0.160**
	(0.018)	(0.022)	(0.018)	(0.012)
Loading ρ on permanent factor μ	6.927**	–12.320**	–1.066**	–7.152**
	(0.360)	(0.237)	(0.218)	(0.112)

Note:
Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level.

Table A4: Parameter Estimates Explaining Initial Medical Care Use

	Any Prescription Drug Use			Any Inpatient Stay			Any Physician Service Use		
Medicaid	0.851	(0.095)	**	0.103	(0.080)		1.027	(0.088)	**
Private without Rx coverage	0.582	(0.091)	**	0.096	(0.082)		1.215	(0.096)	**
Private with Rx coverage	0.657	(0.120)	**	0.071	(0.097)		0.766	(0.117)	**
HMO without Rx coverage	0.663	(0.146)	**	0.155	(0.136)		–0.549	(0.115)	**
HMO with Rx coverage	0.891	(0.089)	**	–0.156	(0.085)	*	–1.187	(0.071)	**
Chronic Condition: Heart/Stroke	1.630	(0.055)	**	1.360	(0.038)	**	0.993	(0.045)	**
Chronic Condition: Respiratory	1.067	(0.090)	**	0.729	(0.042)	**	0.463	(0.064)	**
Chronic Condition: Cancer	0.673	(0.067)	**	0.505	(0.040)	**	0.517	(0.059)	**
Chronic Condition: Diabetes	1.322	(0.083)	**	0.338	(0.041)	**	0.555	(0.057)	**
Age	0.028	(0.010)	**	0.029	(0.008)	**	0.084	(0.009)	**
Age Squared	–0.069	(0.039)	*	–0.042	(0.031)		–0.217	(0.038)	**
Male	–0.594	(0.046)	**	0.133	(0.039)	**	–0.374	(0.044)	**
Education	0.015	(0.011)		–0.004	(0.009)		0.017	(0.011)	
Race: Black	–0.123	(0.083)		–0.131	(0.066)	**	–0.288	(0.074)	**
Race: Hispanic	–0.048	(0.172)		–0.104	(0.144)		–0.324	(0.140)	**
Race: Other nonwhite	–0.247	(0.189)		–0.167	(0.182)		–0.619	(0.166)	**
Marital Status: Widowed	–0.056	(0.054)		0.145	(0.043)	**	–0.114	(0.051)	**
Marital Status: Separated, Divorced, Single	–0.238	(0.083)	**	0.010	(0.074)		–0.402	(0.073)	**
Ln(Income)	0.083	(0.024)	**	–0.048	(0.021)	**	0.102	(0.023)	**
Rural	–0.149	(0.062)	**	0.022	(0.051)		0.204	(0.064)	**
AAPCC Part A	–0.009	(0.005)	*	0.008	(0.004)	*	–0.014	(0.005)	**
AAPCC Part B	0.012	(0.007)	*	0.000	(0.006)		0.002	(0.007)	
Average Prescription Drug Retail Price	–0.010	(0.007)		0.011	(0.005)	**	0.009	(0.006)	
Reside within 100 miles of Canada/Mexico Border	–0.059	(0.059)		–0.064	(0.048)		–0.056	(0.053)	
# of Hospitals/Capita	0.151	(0.148)		0.099	(0.121)		0.060	(0.153)	
# of Hospital Beds/Capita	–0.001	(0.001)		0.000	(0.001)		0.003	(0.002)	
# of MDs/Capita	0.000	(0.002)		0.001	(0.002)		0.001	(0.002)	
Calendar Year	0.077	(0.013)	**	–0.018	(0.011)		–0.141	(0.013)	**
Loading ρ on permanent factor μ	–0.313	(0.113)	**	0.040	(0.078)		–0.504	(0.111)	**

Note:
Standard errors are in parentheses. ** indicates joint significance at the 5% level; * 10% level.
The three demand equations are estimated separately.

Table A5: Parameters Explaining Initial Health Stock
(relative to no functional limitation)

	Severely Disabled	Moderately Disabled
Chronic Condition: Heart/Stroke	1.071**	0.703**
	(0.050)	(0.031)
Chronic Condition: Respiratory	0.886**	0.750**
	(0.060)	(0.041)
Chronic Condition: Cancer	0.381**	0.284**
	(0.056)	(0.038)
Chronic Condition: Diabetes	0.656**	0.344**
	(0.054)	(0.038)
Age	0.078**	0.048**
	(0.007)	(0.005)
Male	–0.741**	–0.673**
	(0.077)	(0.049)
Education	–0.048**	–0.026**
	(0.010)	(0.007)
Race: Black	0.405**	0.161**
	(0.074)	(0.053)
Race: Hispanic	0.068	0.101
	(0.175)**	(0.114)
Race: Other nonwhite	0.033	0.124
	(0.229)	(0.144)
Marital Status: Widowed	–0.073	0.020
	(0.058)	(0.037)
Marital Status: Separated, Divorced, Single	0.190**	0.053
	(0.094)	(0.062)
Ln(Income) Squared	0.746**	0.182**
	(0.184)	(0.066)
Ln(Income) Squared:	–0.558**	–0.220**
	(0.103)	(0.039)
Rural	0.024	0.099**
	(0.055)	(0.036)
Birth Cohort	–0.248**	–0.139**
	(0.063)	(0.040)
Initial Height	–0.459**	–0.133**
	(0.044)	(0.033)
Initial Height Squared	0.348**	0.095**
	(0.035)**	(0.026)
Smoke ever	0.118**	0.131**
	(0.053)	(0.034)
Air Quality	0.005**	0.004**
	(0.002)	(0.002)
Loading ρ on permanent factor μ	0.285**	0.097**
	(0.062)	(0.036)

Note:
Standard errors are in parentheses.
** indicates joint significance at the 5% level; * 10% level.
The parameters are from one multinomial logit model.

Table A6: Factor Loadings and Distribution of Unobserved Individual Heterogeneity

Factor Loading Estimates			Permanent (ρ)			Time-Varying (ω)		
Medical Care Demand Equations								
Any Prescription Drug Expenditures			0.089	(0.116)		2.517	(0.081)	**
Prescription Drug Expenditures, if Any			–0.139	(0.028)	**	0.877	(0.018)	**
Any Hospitalization			0.121	(0.098)		7.351	(0.110)	**
Hospital Expenditures, if Any			–0.019	(0.045)		2.683	(0.055)	**
Any Physician Service Expenditures			–0.504	(0.088)	**	1.618	(0.078)	**
Physician Service Expenditures, if Any			–0.051	(0.045)		3.783	(0.027)	**
Health Production Function								
Die			0.410	(0.071)	**	–3.558	(0.192)	**
Severely Disabled			0.439	(0.052)	**	–1.068	(0.155)	**
Moderately Disabled			0.318	(0.032)	**	–0.804	(0.113)	**
Supplemental Insurance Choice								
Medicaid			8.406	(0.349)	**	0.978	(0.116)	**
Private			–15.664	(0.268)	**	0.485	(0.140)	**
HMO			–1.881	(0.245)	**	–0.387	(0.104)	**
Prescription Drug Coverage (if Private or HMO Supplemental Coverage)			–8.056	(0.108)	**	–0.165	(0.096)	*
Health Shock Probabilities								
Heart/Stroke			–0.384	(0.028)	**	1.000	(—)	
Respiratory			–0.190	(0.063)	**	5.658	(0.266)	**
Cancer			–0.470	(0.055)	**	2.716	(0.171)	**
Initial Condition Equations								
Medicaid			6.927	(0.360)	**			
Private			–12.320	(0.237)	**			
HMO			–1.066	(0.218)	**			
Prescription Drug Coverage (if Private or HMO Supplemental Coverage)			–7.152	(0.112)	**			
Any Prescription Drug Utilization			–0.313	(0.113)	**			
Any Hospitalization			0.040	(0.078)				
Any Physician Service Utilization			–0.504	(0.111)	**			
Severely Disabled			0.285	(0.062)	**			
Moderately Disabled			0.097	(0.036)	**			
Heart/Stroke			–0.119	(0.033)	**			
Respiratory			0.027	(0.045)				
Cancer			–0.141	(0.040)	**			
Diabetes			1.000	(—)				
Heterogeneity Distribution	Mass Point	Weight	Mass Point Estimate			Weight Estimate		
Permanent (μ)	0.000	0.356	-	-		0.020	(0.016)	
	0.589	0.362	0.362	(0.019)	**	–0.234	(0.018)	**
	1.000	0.281	-	-		-	-	
Time-Varying (ν_t)	0.000	0.122	-	-		1.614	(0.026)	**
	0.632	0.611	0.541	(0.011)	**	0.787	(0.046)	**
	1.000	0.267	-	-		-	-	