Health Insurance, Medical Care, and Health Outcomes

A Model of Elderly Health Dynamics

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ABSTRACT

Prescription drug coverage creates a change in medical care consumption, beyond standard moral hazard, arising both from the differential cost-sharing and the relative effectiveness of different types of care. We model the dynamic supplemental health insurance decisions of Medicare beneficiaries, their medical care demand, and subsequent health outcomes over time. Using parameter estimates obtained with longitudinal individual-level data, we simulate behavior under different drug coverage scenarios. Prescription drug coverage increases drug expenditures by 7 percent to 27 percent over a five-year period. While mortality rates fall slightly, the survivors have poorer health, leading to higher total medical expenditures.

I. Introduction

One of the fundamental questions in health economics is how health insurance affects the demand for medical care. In general, health insurance causes ex

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post moral hazard (that is, an increase in the demand for medical care as a result of the decreased net price of care).[1] Moreover, 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 medical care. This change in medical care consumption 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 resulting changes in morbidity and mortality affect all future medical care expenditures. The behavioral effect could lead to more efficient use of medical care resources if increased demand for a newly covered service reduces costly expenditures on 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.

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, more importantly, on the health of the elderly.[2] Unfortunately, we must wait a few years; careful examination of what are obviously dynamic outcomes can occur only at some point in the future. However, existing sources of prescription drug coverage, and health insurance in general, provide insight into the relationships 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 over time.

Our model can be used to understand how prescription drug coverage 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. Increased prescription drug use may reduce disability among the elderly, reduce the onset of chronic illness and its complications, and reduce mortality. This health maintenance or improvement may reduce hospital and physician service 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. Our dynamic analysis allows an increase in prescription drug use induced by drug coverage to affect subsequent total medical care expenditures of the elderly through changes in health status over time. Modeling the health and behavior of

1. Ex ante moral hazard refers to the insurance-induced changes in behaviors that increase a person's probability of needing medical care.

2. In December 2003, the president of the United States 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.

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.

We use data from the longitudinal Medicare Current Beneficiary Survey Data (MCBS) from 1992 to 2001 to jointly estimate a system of dynamic empirical equations representing supplemental insurance coverage decisions, drug and other medical care demand, and health production. Specifically, our findings quantify the effect of prescription drug coverage (through Medicaid, employer and private insurance plans, or Medicare's managed care option) on the demand for drugs as well as hospital and physician services among Medicare beneficiaries. We also examine the effect of each medical care input on chronic condition status, functional status, and mortality, and the effect of health on subsequent medical care consumption over time. We evaluate the long-run (five-year) effect of drug coverage by simulating behavior 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 7–27 percent over five years (depending on the type of drug coverage provided). The associated changes in hospital and physician service expenditures differ depending of the source of drug coverage and the subpopulation of interest, but some offsets in expenditures are realized. While some of the increase in total expenditures is directly attributable to changes in insurance, the increase results from changes in health as well. 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 consumption of other Medicare-covered services.

This paper extends the literature on moral hazard induced by health insurance in several ways. We are the first to model the dynamic effects of insurance and drug coverage on health and Medicare-covered expenditures over time. A few papers have tried to estimate the static effect of prescription drug coverage on other forms of medical care expenditures, but never before in a dynamic framework. Static models miss much of the total effect of prescription drug coverage, because prescription drug use affects future morbidity, mortality, and medical care expenditures, not just current ones. Furthermore, because our model allows for both permanent and time-varying heterogeneity, we show that medical care behavior of the elderly is highly correlated over time. Our policy simulations not only show modest cost offsets over five years, they break down the changes into morbidity and mortality effects.

In Section II we discuss the relevant literature and our contributions. Dynamic 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 the theoretical motivation, our empirical specification, and identification are provided in Section III. The longitudinal data, described in Section IV, are sufficiently rich in both health and medical care information to estimate the dynamic empirical model. In Section V we use 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 VI summarizes our findings.

II. Background and Literature Review

Even before Medicare began offering prescription drug coverage, elderly Americans spent 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). By 2001, the average elderly individual consumed over $1,400 annually in prescription drugs (MCBS data). 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 United States. (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 large demand for drugs, insurance coverage of outpatient prescription drugs was limited among the elderly. Before 2006, the Medicare program did not cover most outpatient prescription drugs. However, about 65 percent of Medicare beneficiaries had some drug coverage from at least one supplemental insurance plan, leaving 35 percent who covered the full cost of outpatient prescription drugs out of pocket. Among those with drug coverage (which may be from multiple sources), about 44 percent had employer-provided health insurance (either as retirees or active workers), 16 percent held privately purchased individual coverage, 16 percent had Medigap insurance, 11 percent were covered through a Medicare managed care plan, 17 percent were on Medicaid, and 4 percent had other publicly provided coverage, including Veteran Assistance or state Pharmacy Assistance (Poisal et al. 1999). Adverse selection suggests, however, that those who purchased additional insurance beyond Medicare were those who expected to have higher than average medical care expenditures.

Although more than half of the Medicare beneficiaries had at least one type of drug coverage, none of these drug insurance plans were comprehensive. Out-of-pocket payment was still the largest source of outpatient drug payment for the elderly, and accounted for 50 percent of total drug expenditures (Poisel et al. 1999). Several studies show that insurance coverage is strongly related to the use of prescription drugs. In a sample of elderly people age 70 and older in the United States, Steinman and colleagues (2001) found that 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 Medicare beneficiaries with coronary heart disease and no drug insurance had lower use of statins (that is, a class of expensive and effective cardiovascular drugs) than those with the disease and prescription drug insurance. Poisal and Murray (2001) found that elderly Medicare beneficiaries with drug coverage received 9 percent more prescriptions on average from 1997 to 1998, while those without any drug coverage received 2.4 percent 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 change consumption over time. Even among those Medicare beneficiaries who had drug insurance, high copayment rates or other cost-sharing limitations may have restricted 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 use. 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 medical care costs and health outcomes. With regard to the effect of drug use on nondrug 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 (2005) found that greater use of clinically essential drugs or newer drugs may decrease the population mortality rate. None of these studies, however, investigated 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 et al. 1997).

An important tradeoff between our dynamic model of individual health behavior and health outcomes over time and a cross-sectional model that explains contemporaneous medical care consumption and perhaps health in one period, is the exclusion versus inclusion of cost-sharing, coverage, and nonpecuniary characteristics of health insurance. Data sets constructed from a one-time interview with individuals may contain more detail with regard to health insurance than those that rely on claims data or individuals being interviewed many times over an extended period. There have been several papers in the health economics literature that address the effects of health insurance characteristics on medical care consumption. What the literature is lacking, however, is an understanding of how medical care utilization in one period affects future medical care utilization, which requires understanding how health evolves over time in light of these consumption decisions. Because medical care consumption depends crucially on health insurance, and unobserved health influences health insurance decisions, medical care use, and subsequent health outcomes, the endogeneity of health insurance must be considered (that is, one should jointly model health insurance decisions). The available longitudinal data that allows us to accomplish our research goals requires that we rely only on indicators of insurance coverage since we do not have (reliable or specific) information on insurance characteristics.

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 associated with prescription drug use may overstate the net cost of the drug benefit given the positive correlation between disability and hospital expenditures among the elderly (Stearns et al. 2007). If the elderly live longer but healthier lives, then total medical care costs 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 may change: 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 consumption, 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.

III. Model of Elderly Health Dynamics

A. 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 (that is, healthy days). Health inputs (medical care and time spent in health producing-activities) augment the natural depreciation of the health stock over time.[3]

3. In the 35 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. Only seven papers to our knowledge (Gilleskie, 1998; Crawford and Shum, 2005; Davis and Foster, 2005; Khwaja, 2001 and 2006; Chan and Hamilton, 2006; and Blau and Gilleskie, 2008) explain medical care and nonmedical input decisions and their influence on health outcomes over time in a manner suggested in health economics' infancy by Grossman. 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.

Much of the empirical work on medical care demand has been based on reduced-form models, or has exploited changes or differences in policies that 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.

Our theoretical framework assumes, like Grossman, that utility is a function of health, but we believe medical care consumption may directly influence current-period utility while also serving as investment in future health. That is, it may alleviate pain, cause discomfort, or capture time costs (which are not modeled directly) associated with utilization. Additionally, we allow prior medical care use to affect current-period utility (and hence, also insurance selection) directly rather than solely through its influence on health transitions from period to period. That is, lagged medical care utilization may alter the marginal utility of medical care this period or influence health insurance purchases from one year to another. Medical care prices, health insurance, and income constrain consumption. We model health shocks each period and allow these observed health shocks to influence contemporaneous consumption and subsequent health transitions. Conditional on health entering the period and health shocks and medical care consumption during the period, the evolution of health from one period to the next is uncertain. Individuals are forward-looking and maximize the sum of contemporaneous utility and discounted expected future utility.

Figure 1 depicts the timing of annual insurance and medical care decisions, health shocks, and health production that characterize our empirical model of individual behavior. An elderly person may choose to supplement basic Medicare insurance coverage with a supplemental plan (I_t) that may or may not include prescription drug coverage (J_t). After choosing his health insurance for the year, he may or may not experience a health shock (S_t). This health shock and his insurance coverage affect medical care consumption during the year. We model demand for hospital services (A_t), physician services (B_t), and prescription drugs (D_t). At the end of the year, health production, which depends on the health shocks and medical care inputs during the year, determines his health next year measured by whether he has ever had particular chronic conditions (E_{t+1}) and his functional status (F_{t+1}).

We denote the information available to an individual at the beginning of each year by $\Omega_t = (E_t, F_t, A_{t-1}, B_{t-1}, D_{t-1}, X_t, Z_t)$. This information set includes observed health entering the period, which is summarized by whether the individual has ever had specific chronic conditions (E_t) and by functional status (F_t) entering period t. A history of medical care use is reflected by the lagged values of medical care demand $(M_{t-1} = [A_{t-1}, B_{t-1}, D_{t-1}])$. Information entering the year also includes exogenous individual characteristics (X_t) and exogenous theoretically relevant variables reflecting price and supply conditions for insurance and medical care (Z_t^I, Z_t^M) and exogenous shifters of health (Z_t^H). Finally, although not denoted here, an individual knows

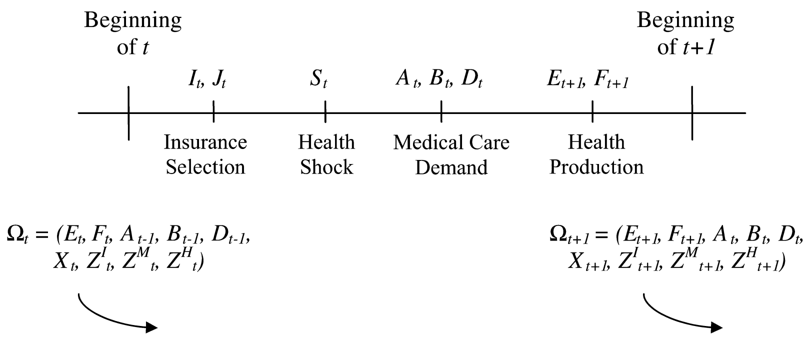

Figure 1
Timing of Annual Decisions, Health Shocks, and Health Production

all current and lagged values of the individual- and time-specific unobserved (by the researcher) components of the optimization problem.

B. Empirical Specification of Jointly Estimated Equations

1. Insurance Selection

All elderly U.S. citizens (age 65 and older) receive Medicare hospitalization coverage (labeled Part A) and have the option to purchase physician services coverage (labeled Part B). Over 95 percent of the elderly choose Part B coverage. Part A coverage is free, but Part B coverage requires a monthly premium. Both Parts A and B are administered as fee-for-service insurance and require some consumer cost sharing in the form of deductibles, co-insurance, indemnity reimbursement, or limits in the amount of coverage. In addition to limits on the number of nights in a hospital and the number of days in a nursing facility following a hospital stay, Medicare Parts A and B do not cover prescription drug use outside of the hospital. Given the cost sharing and limited coverage, some elderly choose to supplement this basic Medicare coverage.

We denote the insurance coverage of an individual covered by Medicare Parts A and B only as $I_t = 0$. By definition, this basic plan does not provide drug coverage so the drug coverage indicator, J_t, equals zero. If eligible, based on state-specific income and asset limits, an individual may be dually covered by Medicare Parts A and B and Medicaid. In this case, denoted by $I_t = 1$, the beneficiary pays no premiums and experiences little or no cost sharing. Medicaid also covers prescription drugs; hence $J_t = 1$ by definition. An individual may choose to supplement basic Medicare coverage with a private plan; we denote this alternative $I_t = 2$. Sources of this private coverage include 12 supplemental options defined by Medicare (termed Medigap plans) and sold by private insurance companies; other privately purchased plans; and employer-provided group plans obtained through a current or former employer, a spouse's employer, or a union. Individuals may select among private plans that do or do not offer prescription drug coverage. Beginning in 1985, Medicare began offering the elderly covered by Parts A and B the option to receive their benefits through a variety of risk-based or coordinated care plans called Medicare+Choice and later renamed Medicare Advantage. This option (labeled $I_t = 3$) is conveniently referred to as Part C, and individuals may choose from an array of managed care plans that do or do not cover prescription drugs. In 2006, Medicare began offering prescription drug coverage (labeled Part D), but the data we use in estimation span the years 1992–2001 only.

The indirect utility of each supplemental plan alternative $i = 0, \ldots, 3$ and each drug coverage alternative $j = 0, 1$ depends on the plan's price (that is, premium), its nonpecuniary characteristics (for example, filing of claims, stigma), the cost-sharing and coverage characteristics associated with that plan, the individual's expectation of his medical care needs (that is, his health during the year), and medical care prices. Together, these determine the beneficiary's out-of-pocket cost distribution. Prior to falling ill and/or consuming medical care, this distribution depends on the information an individual has at the time of insurance purchase. Unfortunately, several aspects of health insurance are not observed by the researcher or do not vary across individuals within a plan, and therefore cannot be included as explanatory variables in estimation.[4] Entering year t, the individual (and the researcher) observes $\Omega_t = (E_t, F_t, A_{t-1}, B_{t-1}, D_{t-1}, X_t, Z_t)$ where $Z_t = \left(Z_t^I, Z_t^H, Z_t^M\right)$. The expected indirect utility of plan i with drug coverage j is

$$(1) \quad V_{ijt}^I = v(E_t, F_t, A_{t-1}, B_{t-1}, D_{t-1}, X_t, Z_t; I_t = i, J_t = j) + u_{ijt}^I$$

where u_{ijt}^I represents unobserved individual heterogeneity that influences insurance decisions.

The observed variation in the arguments of $v(\cdot)$ explains only part of the variation in insurance coverage in the data. Unobserved individual characteristics likely influence the insurance choice, as well as many or all of the behaviors we model, but these unobservables may not be completely idiosyncratic. We decompose the error term, u_{ijt}^I, into three components. The first part, μ, captures permanent, or time-independent, unobserved individual heterogeneity.[5] The second part, ν_t, represents time-varying unobserved individual heterogeneity.[6] The third part, ε_{ijt}^I, is a serially uncorrelated error term that expresses an individual's random preferences for insurance. Let ρ_{ij}^I be the

4. We do not use cost-sharing characteristics of insurance plans, such as co-payments, deductibles, or coinsurance rates, because 1.) they are not available in the MCBS data (for private plans) or 2.) they do not vary across individuals (for the Medicare only option) or vary very little (for Medicaid) or 3.) they vary in too many dimensions to simplify (for Part C plans). The MCBS data do report out-of-pocket costs, as well as claims, which enables the researcher to calculate the percent of total costs paid by the consumer, but does not allow the researcher to uncover the specific cost-sharing structure. Because of potential measurement error, we do not use these constructed variables.

5. Examples of unobserved permanent individual heterogeneity include risk aversion or attitude toward medical treatment. 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.

6. An example of an unobserved characteristic that may vary over time for a particular individual is the unobserved rate of natural deterioration of health. Although medical care consumption may help people 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 of time-varying heterogeneity is an unobserved health shock in any particular year. These time-varying unobservables may affect health insurance selection over time as well as other modeled behaviors.

factor loading on μ and ω_{ij}^{I} be the factor loading on v_t for each insurance option i and j. The error decomposition is

$$(2) \quad u_{ijt}^{I} = \rho_{ij}^{I}\mu + \omega_{ij}^{I}v_t + \varepsilon_{ijt}^{I}$$

where vectors ρ^I, μ, ω^I, and v_t are estimated parameters of the empirical model.[7]

Substituting Equation 2 into Equation 1 and assuming an Extreme Value distribution of the additive idiosyncratic error term (ε_{ijt}^{I}) in the alternative-specific value function for insurance, the individual's decision rule is to choose the combination of insurance plan i and drug coverage j that provides the highest indirect utility. Our assumptions yield a multinomial logit distribution of the polydichotomous supplemental insurance plans as a function of the theoretically relevant variables known by the individual at the beginning of the period.

Private supplemental plans differ from the Part C options regardless of whether the plan offers drug coverage or not (for example, physician choice, cost sharing, etc.) The similarities among plans with different coverage options within the broad insurance categories lead us to model the selection of supplemental insurance type first, and then, conditional on insurance type, the coverage of drugs (Feldman et al. 1989).[8] After approximating the $v(.)$ function with a series expansion of its arguments, the probabilities of dual coverage by Medicaid $(I_t = 1)$, supplemental coverage from a private plan $I_t = 2$, and participation in Medicare Part C $I_t = 3$ are specified (in log odds relative to the basic Medicare plan)[9] as

$$(3) \quad \ln\left[\frac{\Pr(I_t = i)}{\Pr(I_t = 0)}\right] = \eta_{0i} + \eta_{1i}E_t + \eta_{2i}F_t + \eta_{3i}A_{t-1} + \eta_{4i}B_{t-1} + \eta_{5i}D_{t-1}$$
$$+ \eta_{6i}X_t + \eta_{7i}Z_t^I + \eta_{8i}Z_t^H + \eta_{9i}Z_t^M + \eta_{10i}t + \rho_i^I\mu + \omega_i^I v_t,$$
$$i = 1, 2, \text{and } 3.$$

Individuals covered by Medicare Parts A and B only do not have drug coverage; those covered by Medicaid, do. An individual selecting either a private supplemental plan or the Medicare managed-care option *($I_t = 2$ or 3)* may or may not have selected prescription drug coverage. The probability of drug benefits $(J_t = 1)$, relative to no drug benefits, is modeled as a logit outcome where

7. The discrete mass points of the permanent and time-varying heterogeneity distributions are denoted $\mu = (\mu_m, m = 1, \ldots, M)$ and $v_t = (v_{lt}, l = 1, \ldots, L)$, respectively, where M and L are the number of mass points in the discrete approximations to the distributions. Let e represent the equation this unobserved heterogeneity influences. 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.

8. Although our modeling of permanent and time-varying unobserved heterogeneity breaks the assumption of independence of irrelevant alternatives that plagues the multinomial logit specification, we go one step further and model the plan and drug coverage demand using two equations (allowing for unique marginal effects of included explanatory variables across both insurance type and drug coverage) that we estimate jointly (allowing for correlation in unobservables).

9. We express the specification of dichotomous and polychotomous outcome probabilities in log odds only for notational purposes since it avoids writing the argument of the exponential multiple times.

$$(4) \quad \ln\left[\frac{\Pr(J_t = 1|I_t = 2 \text{ or } 3)}{\Pr(J_t = 0|I_t = 2 \text{ or } 3)}\right] = \xi_0 + \xi_1 \boldsymbol{1}[I_t = 3] + \xi_2 E_t + \xi_3 F_t + \xi_4 A_{t-1} + \xi_5 B_{t-1} + \xi_6 D_{t-1} + \xi_7 X_t + \xi_8 Z_t^I + \xi_9 Z_t^H + \xi_{10} Z_t^M + \xi_{11} t + \rho^J \mu + \omega^J v_t.$$

The health insurance decision at the beginning of the period depends on price and supply conditions in the insurance market (Z_t^I) and expected medical care expenses during the coverage period. This expectation is a function of expected health (or need for medical care), expected medical care utilization, and medical care prices. Existing chronic conditions (E_t) and functional status (F_t) entering the period determine the health distribution. Additionally, exogenous differences in health-related variables across counties (Z_t^H), such as measures of air quality, affect the probability of health shocks. Expected utilization during the period depends on lagged indicators of previous medical care use of each type of medical care $(A_{t-1}, B_{t-1}, D_{t-1})$ because we assume these alter the marginal utility of consumption of medical care this period. The demand for a particular type of medical care is a function of its own price, as well as the price of substitutes and compliments. Medical care price and supply variables are summarized by Z_t^M.

We also include time trends to control for aggregate influences that may explain general variation in coverage over time. We allow the observed supplemental health insurance and drug coverage of an individual to be affected by observable individual characteristics (X_t) as well as unobservable individual characteristics (for example, health history or preferences for care), μ and v_t, that are likely to also influence medical care decisions, health shocks, and health transitions. Assumed exogeneity of health insurance and drug coverage decisions would bias estimates of its effect on drug consumption (and other medical care consumption) if such adverse selection occurs. Correct estimates of the effects of insurance are crucial for evaluating the costs and benefits of prescription drug coverage.

2. *Health Shocks*

When an individual enters our sample, we observe whether he has ever had any of the four major chronic health concerns facing the elderly. We define the vector of existing chronic conditions as $E_t = \left(E_t^1, E_t^2, E_t^3, E_t^4\right)$ where E_t^1 indicates heart problems (including high blood pressure, stroke, and heart disease); E_t^2 indicates respiratory problems (such as bronchitis and emphysema); E_t^3 indicates cancer; and E_t^4 indicates diabetes. These chronic conditions tend to be the most disabling among the elderly and the elderly experiencing multiple chronic conditions consume much more medical care (Wolff et al. 2002). It has been suggested that better primary care, especially coordination of care, could reduce avoidable hospitalization rates (Culler et al. 1998). Others maintain, however, that better coordination and management of chronically ill patients may improve quality of care but will not reduce overall treatment costs (Fireman et al. 2004).

We define the onset of these chronic conditions as a health shock. Individuals with a history of these chronic conditions may experience an acute event associated with the condition, which we also define as a health shock. Hence, individuals with or without chronic condition k entering year t may experience a health shock of type k in year t (S_t^k). An adverse health shock among individuals free of disease (that is, $E_t^k = 0$ and $S_t^k = 1$) implies that they have the chronic condition in the subsequent period ($E_{t+1}^k = 1$). We also assume that these conditions are never cured.[10]

Our estimated equation system includes the probability of health shocks of type k where k indicates the particular health shock enumerated above.[11] The logit probability of health shock k, expressed in log odds relative to not having health shock $k$in period t, is

$$(5) \quad \ln\left[\frac{\Pr(S_t^k = 1)}{\Pr(S_t^k = 0)}\right] = \phi_0^k + \phi_1^k E_t + \phi_2^k F_t + \phi_3^k X_t + \phi_4^k Z_t^H + \rho^{Sk}\mu + \omega^{Sk} v_t, k = 1, 2, \text{ and } 3.$$

Variations in existence of chronic conditions and functional status entering the current period ($E_t$and F_t), as well as demographic characteristics (X_t), affect the probability of a health shock. We control for exogenous county and year differences in health-related variables (Z_t^H) that influence onset of or complication from chronic conditions. We assume these exogenous variables have no independent effect on functionality transitions from year to year, once shocks are observed. These health shocks, however, are likely correlated with permanent and time-varying unobservables that determine other health-related behaviors such as insurance selection, medical care demand, and functionality transitions, as indicated by the inclusion of μ and v_t above.

3. *Medical Care Demand*

Observed annual medical care demand depends on the lifetime value of medical care consumption this period. The lifetime value of different hospital services, physician services, and prescription drug levels ($A_t = a, B_t = b$, and $D_t = d$) is comprised of contemporaneous utility and the expected present discounted value of utility in the future conditional on the medical care choices in period t.

Current utility of different medical care combinations depends on this period's selected health insurance coverage (I_t, J_t) and observed health shocks (S_t) as well as chronic condition status (E_t) and functionality (F_t) entering the period. Exogenous prices of (all types of) care (Z_t^M) and individual demographics (X_t) also affect demand. We allow past medical care consumption $(A_{t-1}, B_{t-1}, D_{t-1})$ to influence current consumption partially through pathways other than health. That is, lagged medical care behavior may influence the marginal utility of care today. Some theories of demand suggest that the current utility of consumption of addictive goods may depend on

10. By construction, 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 (E_t,F_t) which affects the probability of a health shock.

11. While we include diabetes as one of the four initially observed chronic conditions, 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 percent). 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.

the use of that good in previous periods (Becker and Murphy 1988; Becker et al. 1994). While we are not suggesting that consumption of medical care is addictive, use 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 followup physician care or prescription medication.

Expected future utility, the second component of the lifetime (indirect) value of medical care consumption this period, depends on the effectiveness of medical care in maintaining or improving health next period (that is, health production) that may be offset by health shocks today. The unobserved natural deterioration of health over time and unobserved health shocks also affect health transitions and hence medical care demand today.

This value function and its arguments are

$$V^M_{abdt}(E_t, F_t, A_{t-1}, B_{t-1}, D_{t-1}, X_t, Z^M_t;\ A_t = a, B_t = b, D_t = d \mid I_t, J_t, S_t). \tag{6}$$

By assumption, variations in observed values of Z^I_t and Z^H_t do not independently affect annual demand conditional on the observed insurance plan and drug coverage chosen at the beginning of the period (I_t, J_t) and the observed health shocks (S_t) during the period.

Our data allow for valuation of total medical care consumption as well as out-of-pocket expenditures. Because, in this analysis, we care about the effect of insurance on the total amount of care consumed and the effect of medical care on health, we model total expenditures in each medical care category. Additionally, out-of-pocket expenditure data are self-reported for some service categories and total expenditures may be more accurate because they are based on actual claims. The distribution of medical expenditures is highly skewed, with some people having zero expenditures. Following much of the literature in health economics, we model annual (log) expenditures as the joint product of the probability of any expenditures (using a logit equation) and the log of expenditures, if any (treated as a continuous outcome). Letting q indicate expenditures on either hospital services (A), physician services (B), or prescription drugs (D), the probability of any such expenditures follows a logit specification, written in log odds, where

$$\begin{aligned}\ln\left[\frac{\Pr(q_t > 0)}{\Pr(q_t = 0)}\right] &= \alpha^q_0 + \alpha^q_1 I_t J_t + \alpha^q_2 S_t + \alpha^q_3 E_t + \alpha^q_4 F_t \\ &\quad + \alpha^q_5 \mathbf{1}[A_{t-1} > 0] + \alpha^q_6 \mathbf{1}[B_{t-1} > 0] + \alpha^q_7 \mathbf{1}[D_{t-1} > 0] \\ &\quad + \alpha^q_8 X_t + \alpha^q_9 Z^M_t + \alpha^q_{10} t + \rho^{q1}\mu + \omega^{q1} v_t, \\ & q = A, B, \text{and}\, D.\end{aligned} \tag{7}$$

Log expenditures on q, if any, are modeled as

$$\ln(q_t \mid q_t > 0) = \delta_0^q + \delta_1^q I_t J_t + \delta_2^q S_t + \delta_3^q E_t + \delta_4^q F_t$$
$$\delta_5^q \mathbf{1}[A_{t-1} > 0] + \delta_6^q \mathbf{1}[B_{t-1} > 0] + \delta_7^q \mathbf{1}[D_{t-1} > 0]$$
$$+ \delta_8^q X_t + \delta_9^q Z_t^M + \delta_{10}^q t + \rho^{q2}\mu + \omega^{q2} v_t,$$
$$q = A, B, \text{ and } D. \tag{8}$$

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 individual-level changes in health or insurance coverage, but a significant amount may be due to exogenous aggregate-level changes in advertising and production of new drugs.

The two-equation specification of demand allows variables of interest to have a different marginal effect on the probability of any expenditures and the log of expenditures. However, we allow for permanent and time-varying unobserved heterogeneity that may be correlated with both outcomes. Additionally, 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 followups 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 estimated jointly (along with insurance, health shocks, and health production) and are correlated through both permanent individual unobservables (μ) and contemporaneous time-varying individual unobservables (v_t).

We recognize another important reason to model serial correlation in individual unobservables. Failure to account for this unobserved heterogeneity may lead to an apparent statistical correlation in medical care demand across time, given our inclusion of lagged medical care use. A major concern, then, is accurately modeling unobserved health because the health measures available in the data may not fully capture the effects of past medical care use solely through the health production function.

4. Health Production

Current health and medical care inputs determine health in the subsequent period through a health production function. In addition to chronic conditions, functional status (F_t) serves as a measure of health at the beginning of the annual observation period t. We measure functional status by limitations with Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) with death as the extreme negative health outcome.[12] Using a multinomial logit model, the functional

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

status outcomes are zero ADL or IADL limitations ($F_{t+1} = 0$), at least one IADL limitation and up to two ADL limitations ($F_{t+1} = 1$), more than two ADL limitations ($F_{t+1} = 2$), and death ($F_{t+1} = 3$). The specification of the health production function, written in log odds relative to no limitations in function, is

$$
\begin{aligned}
(9)\quad \ln\left[\frac{\Pr(F_{t+1}=f)}{\Pr(F_{t+1}=0)}\right] &= \gamma_{0f}+\gamma_{1f}F_t+\gamma_{2f}E_t+\gamma_{3f}S_t+\sum_{k=1}^{3}\gamma_{4f}^{k}E_t^kS_t^k \\
&\quad +(\gamma_{5f}+\gamma_{6f}F_t+\gamma_{7f}S_t+\gamma_{8f}A_t+\gamma_{9f}B_t+\gamma_{10,f}D_t)\mathbf{1}[A_t>0] \\
&\quad +(\gamma_{11,f}+\gamma_{12,f}F_t+\gamma_{13,f}S_t+\gamma_{14,f}A_t+\gamma_{15,f}B_t+\gamma_{16,f}D_t)\mathbf{1}[B_t>0] \\
&\quad +(\gamma_{17,f}+\gamma_{18,f}F_t+\gamma_{19,f}S_t+\gamma_{20,f}A_t+\gamma_{21,f}B_t+\gamma_{22,f}D_t)\mathbf{1}[D_t>0] \\
&\quad +\gamma_{23,f}X_t+\rho_f^F\mu+\omega_f^F\nu_t, \\
f &= 1,2,\text{ and }3.
\end{aligned}
$$

The dynamics of health are captured, in part, by the dependence of one's functional status next period on endogenous values of her functional status in the current period (F_t). The occurrence of health shocks each period (S_t) also influence functionality transitions, and these shocks may be different if the shock captures the onset of a chronic condition $\left(S_t^k = 1, E_t^k = 0\right)$ or a complication associated with a chronic condition $\left(S_t^k = 1, E_t^k = 1\right)$. Additionally, health transitions are dynamic because they depend on medical care consumption in the current period. We also include interactions of functional status and current health shocks with each type of care to allow for a different productive effect of medical care at different levels of health. Theory suggests that health production depends on the amount of medical care used and 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. Because we model total consumption in dollars, we are able to include indicators of any use, but also examine the role of expenditures. We also 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 with future health (and indirectly, future insurance choices and medical care use) and thus appropriately predicting net costs of expanded drug coverage.

5. *Initial Conditions*

In addition to the dynamic equations in our model of jointly estimated behavior (that is, two insurance equations (Equations 3 and 4), three health shock equations (Equations 5), six medical care demand equations (Equations 7 and 8), and one functional status equation (Equation 9), we include several reduced-from equations that explain the initially observed values of existing chronic conditions, supplemental insurance plan and prescription drug coverage, medical care use, and functional status for individuals in their first year of the sample. We cannot model these initial conditions as described above because we do not observe the previous behavior that influences their outcomes. Hence, our initial conditions are reduced-form analogs to the dynamic demand and health production equations and include appropriate variables for identification. The unobserved permanent individual heterogeneity that influences the behaviors modeled above also enters these initial condition equations. Specifications of the initial equations and the estimated likelihood function are provided in the Appendix. There we also provide more detail about the joint estimation procedure.

In summary, our empirical model, consisting of a jointly estimated set of equations, has five key features: (1) observed supplemental plan and drug coverage decisions depend on unobserved individual characteristics that also influence the demand for all forms of medical care (endogenous insurance coverage, adverse selection); (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).

C. 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. As such, all lagged values of exogenous variables serve to identify the system. These include Z_t^I, Z_t^H, and Z_t^M, as well as time-varying individual characteristics in X_t. Similarly, conditional on the unobserved heterogeneity (μ and v_t), lagged values of the endogenous variables also aid identification assuming there is no serial correlation in the remaining errors. Additionally, we include 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 (R_0), which proxies for health during childhood, and period t=0 values of the exogenous time-varying identifying variables (Z_0). (See the Appendix for specification of the initial condition equations.) Height is jointly significant in the initial condition equations, and is 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 (for example, 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 nonlinear nature of the specification. This nonlinearity of the initial condition equations also reduces the number of identifying variables needed for identification.

VI. Data

The Medicare Current Beneficiary Survey (MCBS) is well suited for estimating our dynamic model. The MCBS is a longitudinal survey conducted by the Centers for Medicare and Medicaid Services. Information in the MCBS is provided in two major parts—the survey files and the event files. Each respondent is interviewed three times a year and followed for multiple years. At the first interview, the respondent answer questions about demographics, health insurance, and health status. At the end of each year, usually between September and December, the respondent re-answers questions about health status in order to document changes in health. The event files link Medicare claims to survey-reported medical events and provide date, charge, and source of payment information about each inpatient, outpatient, medical provider, nursing home, home health, and hospice event during the year. Charge and payment information for each prescription or refill is 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 are followed for several years. This longitudinal feature makes it possible to estimate the effect of drug use in one year on subsequent health outcomes and medical care use in the next year. Additionally, new elderly individuals (age 65 and older) are brought into the sample each year ensuring a representative cross-sectional sample composition. However, not all of the respondents are observed for the same number of years. Respondents in early years of the survey were followed for five years; more recent participants were followed for three years. Differences in length of participation are due to sample design and death; there is relatively little attrition due to nonresponse.

Of the 28,906 elderly individuals surveyed between 1992 and 2001, 2,941 were dropped because they were either continuously enrolled in a nursing home, or entered a nursing home during the period of observation.[13] Because expenditures on prescription drugs are not available from the MCBS for people who lived in long-term care facilities, we do not include them in analysis. Table 1 details information on our research sample of 25,935 men and women who contribute 76,321 person-year observations to the analysis.

Measurement of a person's general health 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 and chronic conditions. In the MCBS, a survey of functional status is conducted between September and December in every calendar year. About 40 percent 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 Activity 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 5 percent and rise with age (Figure 2) and deterioration in health. Table 2 details one-year functional status transitions of the elderly over the sample period. This table highlights the extent of movement across disability categories; obviously the transition rates differ by age and other

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

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	76.8
At least 4 years	3,574	13.9
More than 4 years	1,031	4.0
Exactly 2 years	6,022	23.2
Exactly 3 years	16,366	63.1
Exactly 4 years	2,516	9.7
More than 4 years	1,031	4.0
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	

characteristics. About 40 percent of the elderly remain in a given disability 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 percent of the severely disabled dying in a given year. Interestingly, the incidence of health improvement is also significant. Almost 20 percent of the sample experiences improved functionality from one year to the next.

At the initial interview, individuals report whether they have ever had particular chronic conditions; these include cardiovascular or cerebrovascular disease, respiratory disease, cancer, or diabetes. In each year surveyed, the individual may experience medical claims associated with these diseases and identified in the claims-based event files by ICD-9 codes. 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. Case and Paxson (2005) find that differences in morbidity and mortality across genders can be explained by differences in the distribution of chronic conditions. Table 3 summarizes the probability of health shocks conditional on ever experiencing a particular chronic condition.

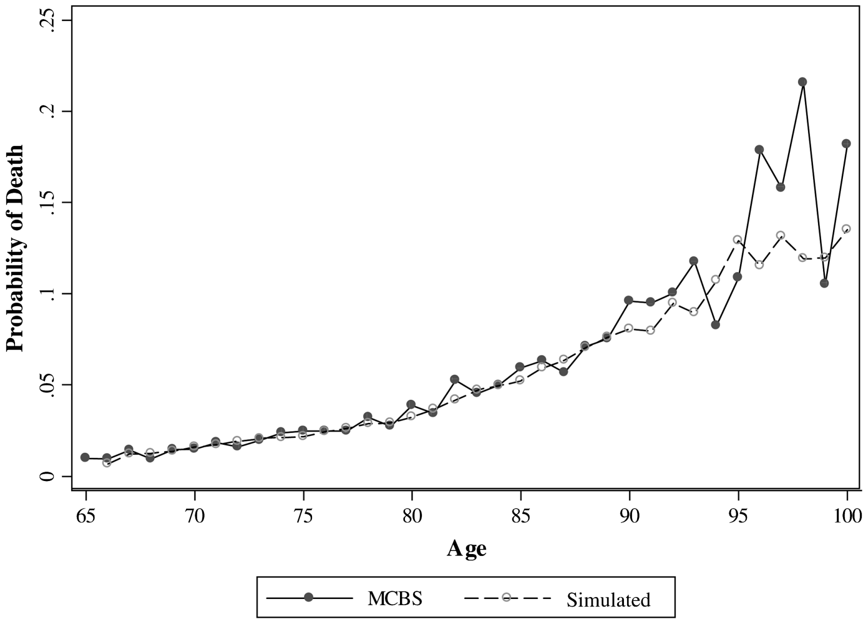

Figure 2
Actual and Simulated Annual Mortality Rates, by Age

Table 4 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 options (Part C plans). In order to measure the effect of third-party coverage of drugs, we distinguish private and Part C plans by whether or not the plan offers outpatient prescription drug coverage. About 13 percent of the Medicare-covered sample respondents were dually covered by Medicaid, which covers prescription drug medication. Almost 50 percent 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.[14] Although the observed probability of prescription drug use by age is nearly constant, expenditures, if any, gradually fall with age (Figure 3a and 3b).[15] 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

14. We adjust all expenditures and income in the sample to year 2001 dollars using the Consumer Price Index.
15. Solid circles represent the observed statistics from the actual sample; we discuss simulated observations indicated by open circles later.

Table 2
Functional Status Transitions

Observed one-year functional status transitions	Functional status in year t+1 (F_{t+1})			
	Not disabled	Moderately disabled	Severely disabled	Die
Functional status in year t (F_t)				
Not disabled (no ADL or IADL)	0.81	0.15	0.02	0.02
Moderately disabled (IADL or up to three ADLs)	0.26	0.57	0.11	0.06
Severely disabled (three or more ADLs)	0.06	0.24	0.56	0.14
Dead	0.00	0.00	0.00	1.00

older ages may be healthier reflecting a negative relationship between medical care expenditures and age among survivors.

Figures 3c and 3d illustrate a similar age pattern for Part A hospital expenditures (conditional on any) with an average of $13,058 per year. However, the probability of hospitalization increases dramatically with age from around 12 percent at age 65 to over 30 percent 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. Use of Part B physician services is uniform by age, as shown in Figures 3e and 3f, but annual expenditures by age exhibit an 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 United States is consumed by individuals in their last year of life (Yang et al. 2003;

Table 3
Health Shocks and Chronic Conditions

Probability of health shock (conditional on existing chronic conditions)[a]	Health shock during year t (S_t)		
	Heart/stroke	Respiratory	Cancer
Chronic condition entering year t (E_t)			
Heart/stroke (ICD-9 390-439)	0.38	0.06	0.06
Respiratory (ICD-9 480-496)	0.32	0.20	0.07
Cancer (ICD-9 140-209)	0.27	0.18	0.06
Diabetes (ICD-9 250)	0.33	0.05	0.06
None	0.01	0.05	0.08

a. A person may have multiple chronic conditions or shocks.

Table 4
Description of Endogenous Variables

Notation	Variable name[a]	Specification	Percent[b]	
I_t	Supplemental insurance plan in t	multinomial		
	Medicare only (no supplement)	logit	8.05	
	Medicaid		11.96	
	Private plan		64.43	
	Part C plan		15.56	
J_t	Prescription drug coverage in t conditional on private or Part C plan	logit	62.99	
S_t	Health shock in t			
	Heart/stroke (ICD-9 390-439)	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 use in t	logit	83.79	
$D_t > 0$	Any prescription drug use in t	logit	89.58	
$A_t \mid A_t > 0$	Hospital expenditures in t	OLS	13057.64	(16900.38)
$B_t \mid B_t > 0$	Physician service expenditures in t	OLS	2013.00	(3359.87)
$D_t \mid D_t > 0$	Prescription drug expenditures in t	OLS	980.12	(1159.48)
F_{t+1}	Functional status entering t+1 (at end of t)	multinomial		
	Not disabled (no ADL or IADLs)	logit	57.74	
	Moderately disabled (IADL or up to three ADLs)		28.05	
	Severely disabled (three or more ADLs)		9.62	
	Dead		4.59	
E_{t+1}	Chronic conditions entering t+1 (at end of t)			
	$E_{t+1} = E_t + S_t$, $t = 1, \ldots, T$			
	$E_1 = E_0$ where E_0 includes shocks at period t=0 [c]			

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 are reported for expenditures. Standard deviations are in parentheses.
c. Statistics for initial condition equations are in Appendix Table A1.

Stearns and Norton 2004). Figure 4 illustrates, by age, the higher average annual expenditures for hospital and physician services among those in their death year than among 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. People who die have fewer days within the calendar year

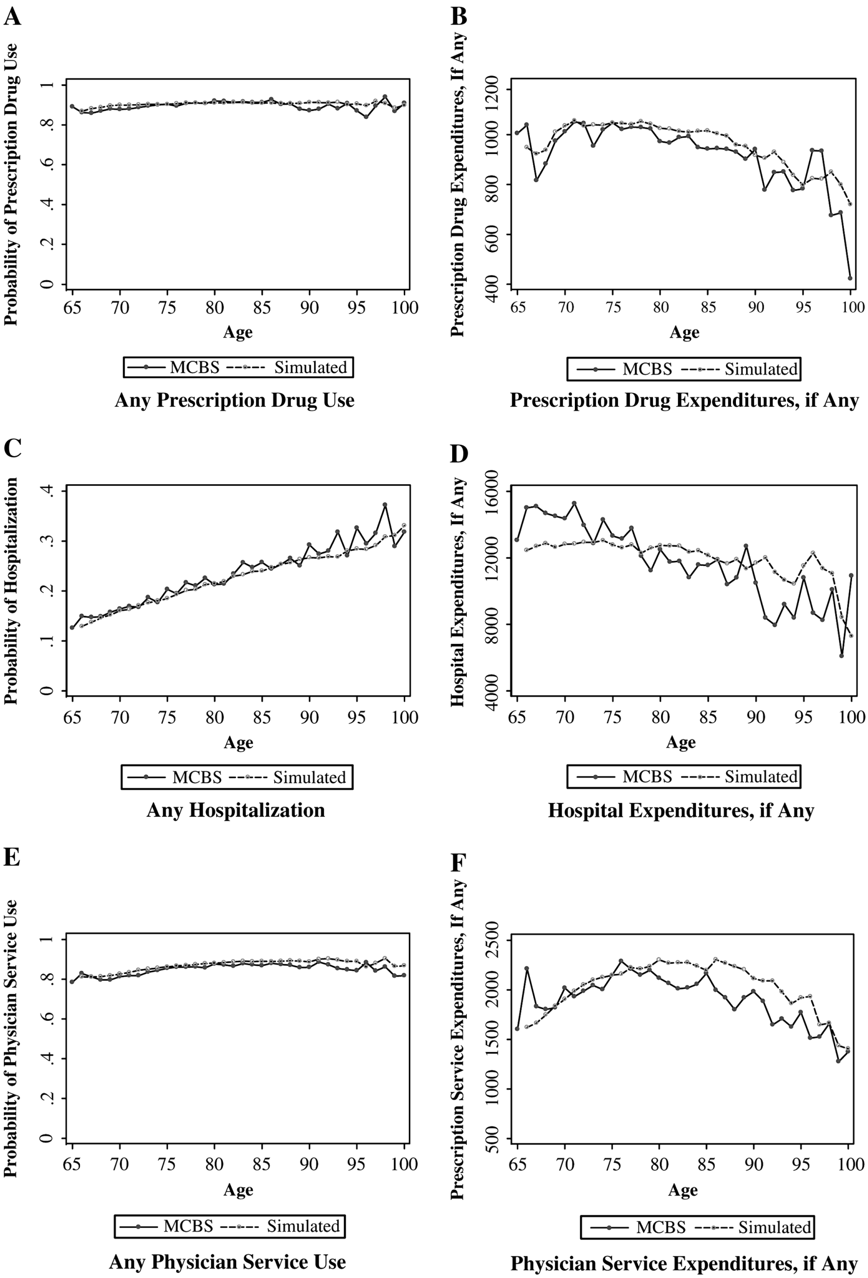

Figure 3
Actual and Simulated Medical Care Use and Expenditures, by Age

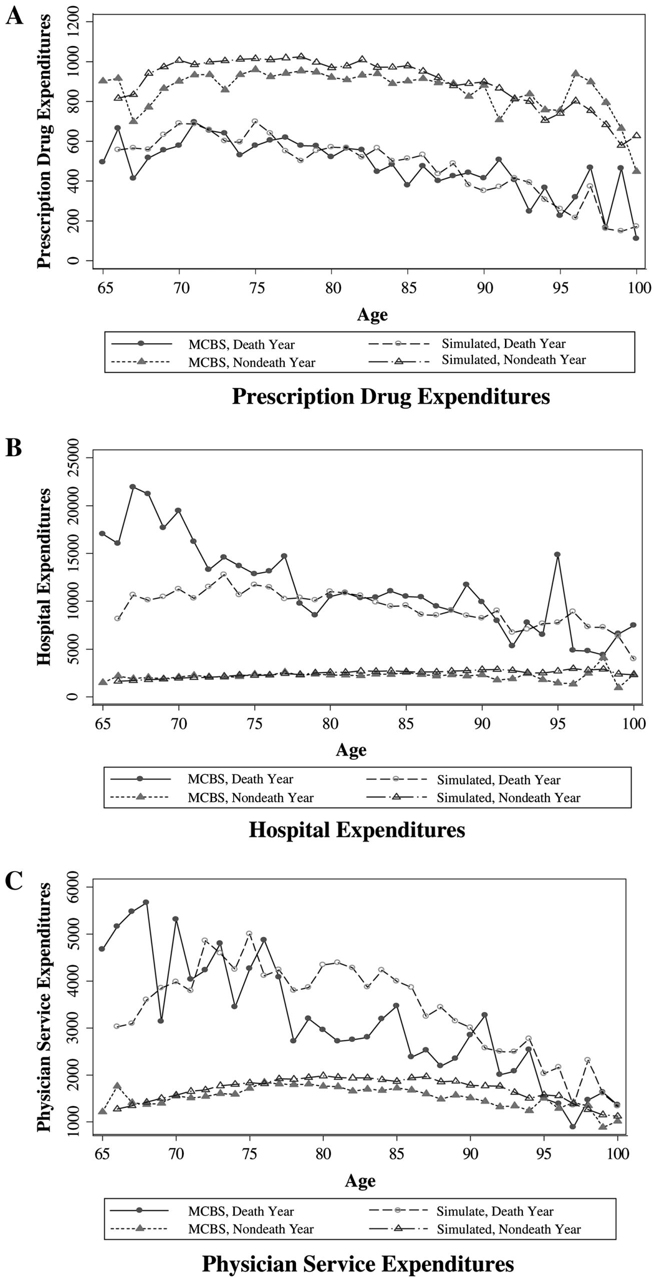

Figure 4
Actual and Simulated Medical Care Expenditures, by Age and Death

Table 5
Description of Exogenous Individual 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 nonwhite	0.01	0.10
Veteran	0.23	0.42
Birth decade (0 = 1900)	1.63	0.81
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 2001 dollars)	26.58	57.49

to consume drugs and may be hospitalized more days out of the year (and receiving inpatient drug treatment) than individuals who survive the entire year.

Table 5 summarizes the individual variables used to explain insurance selection, medical care demand, health shocks, and functional status transitions. In addition to these exogenous variables, the dependent variables defined in Table 4 serve as endogenous explanatory variables in relevant equations. We also include additional exogenous variables that help identify variations in the decision variables and health outcomes (Table 6). Some of these variables capture variation in the supply and price of insurance and medical care during our sample period. 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 (for example, lower (negotiated) prices of medical care services in areas of high managed care concentration). The Area Resource File provides the adjusted average per capita cost (AAPCC) rates for Medicare services, which are based on projected average county-level fee-for-service spending for each upcoming year. The AAPCC rates were used to set Medicare reimbursement rates prior to the Balanced Budget Act of 1997. We obtain average retail prescription drug prices that 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-United States locations. The number of physicians, hospitals, and hospital beds per 1,000 elderly by county and year, also obtained from the Area Resource File, reflect variations in medical care supply conditions. We include the Environmental Protection Agency's measure of median air quality by county and

Table 6
Description of Exogenous Identifying Variables

Role	Variable name	Source of variation	Mean	Standard deviation
Availability/price of insurance	Percent of county HMO enrolled; HMO penetration[a]	county, year	18.91	14.14
Price of hospitalization	Medicare AAPCC part A rate[b]	county, year	350.07	230.75
Price of physician services	Medicare AAPCC part B rate[b]	county, year	226.56	140.53
Price of prescription drugs	Average prescription drug retail price[c]	state, year	41.01	5.49
Price of prescription drugs	Reside within 100 miles of Canadian or Mexican border[d]	zip code, year	0.17	0.37
Supply of physicians	Number of physicians / 1000 elderly[b]	county, year	18.01	14.26
Supply of hospitals	Number of hospitals / 1000 elderly[b]	county, year	0.18	0.18
Supply of hospital beds	Number of hospitals beds / 1000 elderly[b]	county, year	30.52	22.12
Exogenous shift in health	Median air quality index[e]	county, year	34.79	11.04
Exogenous variable in initial conditions	Initial height in inches	individual	65.67	3.99

a. We thank Lawrence Baker for measures of HMO penetration per county.
b. The projected average county-level fee-for-service spending for the coming year, or adjusted average per capita cost (AAPCC) rates, were used to set Medicare reimbursement rates prior to the Balanced Budget Act of 1997. These values and the physicians, hospital, and bed supply numbers are from the Area Resource Files.
c. Drug prices are the total value of drug costs divided by the total number of drugs sold in a particular state and year.
d. Distance to border is calculated using zip code centroids and North America Equidistant Conic map projections.
e. The median air quality index is reported for counties by the Environmental Protection Agency. Higher values indicate worse air quality.

year, where increasing values of the index indicate lower air quality, to capture changes in exogenous measures that may influence health.

V. Discussion

Using the MCBS panel data we jointly estimate our model of elderly health behavior over time. The complexity of this dynamic system of demand equations and health production with its feed-forward structure suggests analysis of the estimation results on several levels. In Section VA, we discuss the signs and significance of the main explanatory variables of interest in each equation, which qualitatively describes the short-run effects.[16] We also compare our results to those from estimation of single equations where we do not account for the endogeneity of important lagged choices or outcomes such as insurance, medical care inputs, and health on subsequent behavior. In Section VB, we discuss results from a five-year simulation of the system of jointly estimated equations in order to illustrate the influence of particular variables in the long run, taking into account changes in health status and mortality over time.

A. Estimation Results

1. Effects of insurance on medical care demand

We begin by discussing the effect of insurance on prescription drug consumption because this relationship is at the heart of our analysis. In our preferred model (that is, 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 both whether a person uses any prescription drugs (Table 7a, second column) and the log of expenditures for those who use any (Table 7a, fourth column). The signs of coefficients on other variables are generally in the expected direction, with current health shocks, functional limitations, and existing chronic conditions each increasing use of and expenditures on prescription drugs. Interestingly, individuals experiencing cancer-related health shocks in the current period are less likely to use drugs and spend less on drugs.

Drug coverage, specifically, has little influence on the probability or (log) level of hospital expenditures (Table 7b, second and fourth columns). However, a Medicare Part C plan is associated with a greater probability of hospitalization, but lower expenditures among those with any inpatient stay. Health shocks have a large positive effect on hospital services consumption. Disability and existing chronic conditions are associated with more hospital care. Supplemental insurance coverage by Medicaid or private plans is positively related to physician services consumption, while the Part C plans are associated with lower consumption of physician services (Table 7c, second and fourth columns). This relationship supports the efforts by managed care organizations to reduce medical care costs among its members through early detection and controlled spending. The influences of current health shocks, disability, and existing chronic conditions are positive and significant.

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

Table 7a
Parameter Estimates for Selected Variables Explaining Prescription Drug Expenditures

	Any Prescription Drug Use		Prescription Drug Expenditures, if any	
Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Supplemental insurance in year *t*				
Medicaid	0.407 (0.082)**	0.318 (0.089)**	0.210 (0.026)**	0.158 (0.027)**
Private plan without Rx coverage	0.326 (0.067)**	0.345 (0.102)**	0.093 (0.023)**	–0.017 (0.032)
Private plan with Rx coverage	0.377 (0.066)**	0.462 (0.148)**	0.353 (0.023)**	0.168 (0.046)**
Part C plan without Rx coverage	0.362 (0.122)**	0.445 (0.131)**	0.059 (0.041)	0.065 (0.042)
Part C plan with Rx coverage	0.713 (0.078)**	0.857 (0.093)**	0.121 (0.026)**	0.106 (0.029)**
Health shocks during year *t*				
Heart/stroke	1.088 (0.069)**	0.780 (0.071)**	0.262 (0.013)**	0.202 (0.013)**
Respiratory	0.559 (0.140)**	–0.149 (0.146)	0.139 (0.026)**	–0.044 (0.027)
Cancer	0.316 (0.101)**	–0.196 (0.106)*	0.041 (0.023)*	–0.069 (0.024)**
Functional status entering year *t*				
Moderately disabled	0.202 (0.049)**	0.244 (0.052)**	0.272 (0.013)**	0.278 (0.013)**
Severely disabled	0.047 (0.080)	0.083 (0.084)	0.307 (0.019)**	0.319 (0.020)**
Chronic conditions entering year *t*				
Heart/stroke	0.632 (0.044)**	0.693 (0.048)**	0.355 (0.012)**	0.373 (0.012)**
Respiratory	0.332 (0.066)**	0.448 (0.071)**	0.228 (0.015)**	0.263 (0.015)**
Cancer	0.060 (0.053)	0.073 (0.056)	0.013 (0.014)	0.025 (0.014)*
Diabetes	0.668 (0.064)**	0.673 (0.067)**	0.360 (0.013)**	0.356 (0.013)**

(*continued*)

Table 7a (*continued*)

Selected variables	Any Prescription Drug Use: Single equation without unobserved heterogeneity	Any Prescription Drug Use: 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
Medical care use last year *t*-1				
Any hospitalization	−0.358 (0.061)**	−0.394 (0.064)**	0.058 (0.014)**	0.054 (0.014)**
Any physician service use	0.567 (0.046)**	0.648 (0.049)**	0.196 (0.018)**	0.208 (0.019)**
Any prescription drug use	2.994 (0.040)**	3.220 (0.048)**	1.711 (0.026)**	1.778 (0.026)**
Unobserved heterogeneity				
Loading ρ on permanent factor μ	——	–0.075 (0.136)	——	0.180 (0.041)**
Loading ω on time-varying factor υ_t	——	2.474 (0.085)**	——	0.876 (0.026)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level.
Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

Table 7b

Parameter Estimates for Selected Variables Explaining Hospital Expenditures

Selected variables	Any Hospitalization		Hospital 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 in year *t*				
Medicaid	0.049 (0.059)	0.318 (0.089)**	0.027 (0.042)	–0.043 (0.043)
Private plan without Rx coverage	0.065 (0.054)	0.345 (0.102)**	0.032 (0.039)	–0.015 (0.051)
Private plan with Rx coverage	0.012 (0.053)	0.462 (0.148)**	0.048 (0.039)	0.028 (0.071)
Part C plan without Rx coverage	0.143 (0.101)	0.445 (0.131)**	–0.274 (0.075)**	–0.127 (0.073)*
Part C plan with Rx coverage	0.301 (0.062)**	0.857 (0.093)**	–0.280 (0.046)**	–0.138 (0.049)**
Health shocks during year *t*				
Heart/stroke	1.959 (0.028)**	2.289 (0.043)**	0.185 (0.020)**	0.347 (0.022)**
Respiratory	1.633 (0.054)**	0.631 (0.083)**	0.158 (0.028)**	–0.140 (0.033)**
Cancer	1.283 (0.048)**	0.880 (0.069)**	0.244 (0.028)**	0.195 (0.031)**
Functional status entering year *t*				
Moderately disabled	0.323 (0.030)**	0.487 (0.040)**	0.032 (0.021)	0.104 (0.023)**
Severely disabled	0.649 (0.042)**	0.976 (0.057)**	0.069 (0.028)**	0.210 (0.029)**
Chronic conditions entering year *t*				
Heart/stroke	–0.077 (0.029)**	0.087 (0.037)**	0.018 (0.021)	0.082 (0.022)**
Respiratory	–0.060 (0.036)	0.261 (0.048)**	0.001 (0.024)	0.139 (0.026)**
Cancer	–0.017 (0.032)	0.147 (0.042)**	–0.011 (0.022)	0.059 (0.023)**
Diabetes	0.206 (0.031)**	0.319 (0.040)**	0.056 (0.021)**	0.105 (0.023)**

(*continued*)

Table 7b (*continued*)

Selected variables	Any Hospitalization: Single equation without unobserved heterogeneity	Any Hospitalization: Multiple equations with unobserved heterogeneity	Hospital Expenditures, if any: Single equation without unobserved heterogeneity	Hospital Expenditures, if any: Multiple equations with unobserved heterogeneity
Medical care use last year *t*-1*1*				
Any hospitalization	0.674 (0.031)**	0.896 (0.041)**	0.116 (0.021)**	0.217 (0.022)**
Any physician service use	–0.211 (0.045)**	–0.208 (0.060)**	–0.078 (0.035)**	–0.078 (0.034)**
Any prescription drug use	0.307 (0.054)**	0.390 (0.070)**	–0.015 (0.043)	0.045 (0.039)
Unobserved heterogeneity				
Loading ρ on permanent factor μ	—	−0.233 (0.123)*	—	0.002 (0.006)
Loading ω on time-varying factor υ_t	—	7.481 (0.203)**	—	2.803 (0.069)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level.
Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

Table 7c
Parameter Estimates for Selected Variables Explaining Physician Service Expenditures

	Any Physician Service Use		Physician Service Expenditures, if any	
Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Supplemental insurance in year *t*				
Medicaid	0.529 (0.071)**	0.461 (0.075)**	0.338 (0.032)**	0.211 (0.036)**
Private plan without Rx coverage	0.930 (0.063)**	0.953 (0.093)**	0.271 (0.028)**	0.228 (0.042)**
Private plan with Rx coverage	0.763 (0.059)**	0.818 (0.131)**	0.276 (0.028)**	0.269 (0.063)**
Part C plan without Rx coverage	–0.720 (0.090)**	–0.704 (0.096)**	–0.382 (0.057)**	–0.347 (0.058)**
Part C plan with Rx coverage	–1.117 (0.061)**	–1.100 (0.072)**	–0.534 (0.036)**	–0.475 (0.043)**
Health shocks during year *t*				
Heart/stroke	2.689 (0.102)**	2.531 (0.101)**	0.946 (0.016)**	0.697 (0.015)**
Respiratory	1.598 (0.188)**	1.118 (0.192)**	0.675 (0.031)**	–0.132 (0.035)**
Cancer	2.825 (0.243)**	2.467 (0.244)**	1.092 (0.028)**	0.620 (0.030)**
Functional status entering year *t*				
Moderately disabled	0.053 (0.041)	0.068 (0.042)	0.195 (0.016)**	0.213 (0.016)**
Severely disabled	–0.006 (0.066)	0.035 (0.069)	0.339 (0.024)**	0.380 (0.024)**
Chronic conditions entering year *t*				
Heart/stroke	0.178 (0.036)**	0.190 (0.038)**	0.072 (0.015)**	0.136 (0.015)**
Respiratory	0.109 (0.051)**	0.171 (0.053)**	0.160 (0.019)**	0.310 (0.020)**
Cancer	0.062 (0.045)	0.071 (0.047)	0.118 (0.017)**	0.170 (0.017)**
Diabetes	0.204 (0.045)**	0.207 (0.048)**	0.254 (0.017)**	0.242 (0.017)**

(*continued*)

Table 7c (*continued*)

Selected variables	Any Physician Service Use		Physician Service Expenditures, if any	
	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Medical care use last year *t*-1				
Any hospitalization	−0.083 (0.052)	−0.093 (0.054)*	0.311 (0.018)**	0.298 (0.017)**
Any physician service use	2.323 (0.036)**	2.440 (0.040)**	0.617 (0.029)**	0.736 (0.028)**
Any prescription drug use	0.758 (0.044)**	0.730 (0.046)**	0.486 (0.026)**	0.400 (0.026)**
Unobserved heterogeneity				
Loading ρ on permanent factor μ	—	–0.042 (0.121)	—	–0.017 (0.054)
Loading ω on time-varying factor υ_t	—	1.619 (0.094)**	—	3.779 (0.029)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level.
Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

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 (that is, 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 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 in the medical care demand equations 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 (last two rows of Tables 7a–7c). The time-varying heterogeneity exhibits significance uniformly in these demand equations, whereas the permanent heterogeneity is often insignificant. This pattern suggests that our measures of health are good predictors of general health (or one's health stock), and that the time-varying heterogeneity picks up omitted health shocks that increase per-period demand. This importance of time-varying heterogeneity supports a main feature of our model: joint estimation of medical care demand equations.

2. *Effects of medical care consumption on health production*

We turn now to coefficient estimates on variables that influence health production (Tables 8a–8c). The importance of modeling this equation jointly with the expenditure equations (and health shocks) is to capture correlation in the error terms associated with endogenous medical care inputs that affect health. Such correlation is confirmed if the marginal effects of the endogenous inputs differ when unobserved heterogeneity is modeled and when it is not. With the caveat that specific parameter estimates are hard to compare across the two models, 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 even greater when prescription drugs are used in combination with other types of medical care, suggesting that they are complements. If we believe that differences in expenditures reflect differences in consumption levels only, then additional prescription drug use may maintain current health levels or prevent transitions to worse health. However, we recognize that higher expenditures may reflect differences in quality, not quantity.

While hospital and physician service expenditures appear to reduce health (that is, increase the probability of being in a worse health state), this effect is moderated (where significant) for individuals with greater functional limitations and particular health shocks. In fact, physician services have positive effects on health in some cases. For example, consumption of physician services at levels below $2,500

Table 8a
Parameter Estimates for Selected Variables Explaining Functional Status Transitions

Outcome: (relative to no functional limitation)	Die	
Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Functional status entering year *t*		
Moderately disabled	1.618 (0.196)**	1.551 (0.195)**
Severely disabled	3.987 (0.305)**	3.933 (0.310)**
Chronic conditions entering year *t*		
Heart/stroke	0.746 (0.060)**	0.665 (0.062)**
Respiratory	0.697 (0.069)**	0.593 (0.072)**
Cancer	0.419 (0.061)**	0.370 (0.062)**
Diabetes	0.633 (0.063)**	0.570 (0.065)**
Health shock during year *t*		
Heart/stroke	2.373 (0.387)**	2.212 (0.403)**
Respiratory	0.996 (0.744)	1.183 (0.679)*
Cancer	3.358 (0.841)**	3.336 (0.692)**
Medical care use and log expenditures during year *t*		
Any hospitalization	–1.367 (0.396)**	–1.690 (0.400)**
Hospital expenditures	0.389 (0.051)**	0.501 (0.056)**
Any physician service use	–0.512 (0.200)**	–1.403 (0.253)**
Physician service expenditures	–0.031 (0.037)	0.179 (0.053)**
Any prescription drug use	1.667 (0.179)**	1.556 (0.179)**
Prescription drug expenditures	–0.444 (0.034)**	–0.399 (0.034)**

Interaction of functional status and medical care use		
Moderately disabled x Any hospitalization	0.042 (0.136)	0.050 (0.134)
Moderately disabled x Any physician services	–0.117 (0.173)	–0.136 (0.172)
Moderately disabled x Any prescription drugs	0.343 (0.189)*	0.357 (0.189)*
Severely disabled x Any hospitalization	–0.656 (0.200)**	–0.641 (0.200)**
Severely disabled x Any physician services	0.164 (0.258)	0.103 (0.259)
Severely disabled x Any prescription drugs	0.131 (0.305)	0.121 (0.309)
Interaction of health shocks and medical care use		
Heart/stroke x Any hospitalization	–0.549 (0.136)**	–0.541 (0.136)**
Heart/stroke x Any physician services	–0.684 (0.335)**	–0.643 (0.345)*
Heart/stroke x Any prescription drugs	–0.897 (0.225)**	–0.923 (0.228)**
Respiratory x Any hospitalization	–0.109 (0.268)	–0.173 (0.269)
Respiratory x Any physician services	–0.756 (0.640)	–0.809 (0.624)
Respiratory x Any prescription drugs	–0.040 (0.412)	0.010 (0.448)
Cancer x Any hospitalization	0.051 (0.189)	0.043 (0.189)
Cancer x Any physician services	–2.411 (0.802)**	–2.442 (0.658)**
Cancer x Any prescription drugs	0.067 (0.294)	0.083 (0.298)
Interaction of different types of medical care log expenditures		
Hospital x Prescription drug	–0.007 (0.003)**	–0.007 (0.003)**
Hospital x Physician service	0.015 (0.003)**	0.008 (0.003)**
Physician service x Prescription drug	–0.007 (0.005)	–0.009 (0.004)**
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	–0.321 (0.074)**
Loading ω on time-varying factor υ_t	—	–1.464 (0.273)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level.
Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

Table 8b
Parameter Estimates for Selected Variables Explaining Functional Status Transitions

Outcome: (relative to no functional limitation)	Severely Disabled	
Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Functional status entering year *t*		
Moderately disabled	3.809 (0.354)**	3.789 (0.356)**
Severely disabled	6.774 (0.409)**	6.764 (0.414)**
Chronic conditions entering year *t*		
Heart/stroke	0.223 (0.045)**	0.200 (0.047)**
Respiratory	0.211 (0.056)**	0.177 (0.058)**
Cancer	0.062 (0.051)	0.050 (0.052)
Diabetes	0.359 (0.049)**	0.342 (0.050)**
Health shock during year *t*		
Heart/stroke	0.930 (0.603)	0.903 (0.666)
Respiratory	1.034 (0.942)	1.064 (0.764)
Cancer	3.383 (1.136)**	3.356 (0.911)**
Medical care use and log expenditures during year *t*		
Any hospitalization	–0.201 (0.380)	–0.327 (0.384)
Hospital expenditures	0.082 (0.054)	0.116 (0.056)**
Any physician service use	–0.647 (0.201)**	–0.902 (0.243)**
Physician service expenditures	0.096 (0.036)**	0.159 (0.048)**
Any prescription drug use	0.104 (0.349)	0.026 (0.356)
Prescription drug expenditures	0.240 (0.034)**	0.258 (0.035)**

Interaction of functional status and medical care use		
Moderately disabled x Any hospitalization	–0.474 (0.117)**	–0.472 (0.114)**
Moderately disabled x Any physician services	–0.309 (0.190)	–0.321 (0.187)*
Moderately disabled x Any prescription drugs	–0.779 (0.350)**	–0.772 (0.353)**
Severely disabled x Any hospitalization	–1.295 (0.176)**	–1.283 (0.172)**
Severely disabled x Any physician services	–0.193 (0.252)	–0.223 (0.249)
Severely disabled x Any prescription drugs	–0.683 (0.406)	–0.689 (0.412)
Interaction of health shocks and medical care use		
Heart/stroke x Any hospitalization	–0.267 (0.103)**	–0.265 (0.103)**
Heart/stroke x Any physician services	–0.223 (0.480)	–0.223 (0.519)
Heart/stroke x Any prescription drugs	–0.673 (0.395)*	–0.689 (0.407)*
Respiratory x Any hospitalization	–0.017 (0.184)	–0.035 (0.185)
Respiratory x Any physician services	–0.029 (0.816)	–0.053 (0.715)
Respiratory x Any prescription drugs	–0.887 (0.568)	–0.849 (0.646)
Cancer x Any hospitalization	–0.023 (0.175)	–0.023 (0.175)
Cancer x Any physician services	–3.174 (0.991)**	–3.176 (0.782)**
Cancer x Any prescription drugs	–0.252 (0.598)	–0.235 (0.601)
Interaction of different types of medical care log expenditures		
Hospital x Prescription drug	0.003 (0.004)	0.002 (0.004)
Hospital x Physician service	0.013 (0.003)**	0.012 (0.003)**
Physician service x Prescription drug	0.001 (0.005)	0.000 (0.005)
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	–0.330 (0.058)**
Loading ω on time-varying factor υ_t	—	–0.445 (0.223)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level.
Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

Table 8c

Parameter Estimates for Selected Variables Explaining Functional Status Transitions

Outcome: (relative to no functional limitation)	Moderately Disabled	
Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Functional status entering year *t*		
Moderately disabled	2.490 (0.106)**	2.483 (0.107)**
Severely disabled	2.741 (0.286)**	2.746 (0.291)**
Chronic conditions entering year *t*		
Heart/stroke	0.183 (0.027)**	0.175 (0.028)**
Respiratory	0.306 (0.036)**	0.296 (0.037)**
Cancer	0.108 (0.032)**	0.104 (0.033)**
Diabetes	0.234 (0.032)**	0.229 (0.032)**
Health shock during year *t*		
Heart/stroke	0.257 (0.366)	0.269 (0.376)
Respiratory	0.077 (0.660)	0.057 (0.595)
Cancer	1.499 (0.876)*	1.499 (0.731)**
Medical care use and log expenditures during year *t*		
Any hospitalization	–0.256 (0.271)	–0.313 (0.273)
Hospital expenditures	0.064 (0.037)*	0.075 (0.038)**
Any physician service use	–0.344 (0.082)**	–0.406 (0.115)**
Physician service expenditures	0.076 (0.018)**	0.094 (0.026)**
Any prescription drug use	–0.468 (0.102)**	–0.506 (0.104)**
Prescription drug expenditures	0.180 (0.018)**	0.186 (0.019)**

Interaction of functional status and medical care use		
Moderately disabled x Any hospitalization	–0.301 (0.067)**	–0.300 (0.068)**
Moderately disabled x Any physician services	–0.146 (0.079)*	–0.153 (0.079)*
Moderately disabled x Any prescription drugs	–0.203 (0.106)*	–0.199 (0.106)*
Severely disabled x Any hospitalization	–0.640 (0.163)**	–0.631 (0.161)**
Severely disabled x Any physician services	–0.174 (0.210)	–0.188 (0.210)
Severely disabled x Any prescription drugs	0.106 (0.284)	0.096 (0.289)
Interaction of health shocks and medical care use		
Heart/stroke x Any hospitalization	–0.023 (0.072)	–0.021 (0.072)
Heart/stroke x Any physician services	–0.278 (0.293)	–0.290 (0.302)
Heart/stroke x Any prescription drugs	–0.010 (0.237)	–0.020 (0.239)
Respiratory x Any hospitalization	0.080 (0.122)	0.074 (0.122)
Respiratory x Any physician services	–0.201 (0.532)	–0.200 (0.499)
Respiratory x Any prescription drugs	0.182 (0.450)	0.212 (0.486)
Cancer x Any hospitalization	0.178 (0.113)	0.179 (0.113)
Cancer x Any physician services	–1.526 (0.834)*	–1.540 (0.696)**
Cancer x Any prescription drugs	–0.015 (0.313)	–0.006 (0.314)
Interaction of different types of medical care log expenditures		
Hospital x Prescription drug	0.004 (0.002)*	0.004 (0.003)
Hospital x Physician service	0.001 (0.002)	0.000 (0.002)
Physician service x Prescription drug	–0.003 (0.002)	–0.003 (0.003)
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	–0.212 (0.036)**
Loading ω on time-varying factor υ_t	—	–0.118 (0.122)

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level.
Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

annually significantly reduces the probability of death for nondisabled and moderately disabled individuals and those with health/stroke or cancer shocks in the current period.

The negative signs of the permanent and time-varying factor loadings indicate reduced probabilities of falling into worse health from one period to the next. This is not inconsistent with the interpretation of worse unobserved time-varying health in the demand equations (if we had to attempt to label it) as the latter may reflect relatively innocuous unobserved health shocks requiring medical attention that lead to temporary health declines among generally healthier people. We contend that another feature of our model is warranted: joint estimation of endogenous medical care inputs and health outcomes.

3. Effects of previous medical care consumption on current consumption

Next, we investigate the effect of lagged medical care use on current expenditures. Serial correlation in medical care use 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 7a–7c, for example, we find that lagged medical care use significantly affects medical care consumption today. Previous prescription drug and physician services use are positively serially correlated with contemporaneous drug and physician services consumption, while hospitalization in a previous year suggests a lower probability of any use of these the following year, but greater expenditures if any. Individuals who have been hospitalized or used prescription drugs in the previous year are more likely to be hospitalized this year, but physician services consumption appears to reduce the need for hospital services in the subsequent year.

These estimates suggest that previous medical care 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 (health shocks, functional status, and existing chronic conditions) and the unobserved permanent and time-varying heterogeneity. If our efforts have been unsuccessful then lagged medical care consumption may, in part, capture unmeasured health. Alternatively, its significance may reflect the habitual or dependent nature of medical care use at older ages or an established relationship with a provider that results in continuous care independent of ill health. We maintain, however, that our results confirm importance of this feature of our preferred model: direct effects of lagged behavior. These findings will have significant effects on the long-run cost projections associated with a Medicare drug benefit.

4. Additional Results

Coefficient estimates on selected variables describing supplemental insurance selection, prescription drug coverage, and health shocks are provided in Tables 9, 10, and 11. We note that lagged medical care use is, in general, a significant (positive) predictor of supplemental insurance coverage, with any physician service use in the past making Part C coverage less probable. In addition to defining expectations of future expenditures, lagged medical care consumption may increase eligibility for Medicaid. The influence of unobserved heterogeneity in the supplemental insurance equations suggests that those to the right of the distribution of the unobservables

Table 9
Parameter Estimates for Selected Variables Explaining Supplemental Insurance (relative to Medicare only)

Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Outcome: Medicaid		
Functional status entering year *t*		
Moderately disabled	0.286 (0.052)**	0.335 (0.057)**
Severely disabled	0.563 (0.072)**	0.668 (0.081)**
Chronic conditions entering year *t*		
Heart/stroke	0.207 (0.048)**	0.186 (0.053)**
Respiratory	0.303 (0.060)**	0.303 (0.067)**
Cancer	–0.028 (0.058)	0.009 (0.065)
Diabetes	0.271 (0.053)**	0.203 (0.062)**
Medical care use last year *t-1*		
Any hospitalization	0.147 (0.060)**	0.154 (0.066)**
Any physician service use	0.507 (0.067)**	0.464 (0.073)**
Any prescription drug use	0.441 (0.074)**	0.447 (0.081)**
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	7.692 (0.415)**
Loading ω on time-varying factor υ_t	—	0.850 (0.129)**
Outcome: Private Plan		
Functional status entering year *t*		
Moderately disabled	–0.214 (0.043)**	–0.210 (0.086)**
Severely disabled	–0.387 (0.063)**	–0.627 (0.133)**
Chronic conditions entering year *t*		
Heart/stroke	0.030 (0.039)	–0.040 (0.089)
Respiratory	0.008 (0.051)	–0.105 (0.119)
Cancer	0.109 (0.047)**	0.046 (0.107)
Diabetes	–0.021 (0.046)	–0.884 (0.114)**
Medical care use last year *t-1*		
Any hospitalization	0.078 (0.051)	0.162 (0.097)
Any physician service use	1.035 (0.051)**	1.496 (0.115)**
Any prescription drug use	0.389 (0.054)**	0.377 (0.131)**
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	24.590 (0.546)**
Loading ω on time-varying factor υ_t	—	0.606 (0.173)**
Outcome: Part C Plan		
Functional status entering year *t*		
Moderately disabled	–0.203 (0.051)**	–0.158 (0.063)**
Severely disabled	–0.449 (0.079)**	–0.526 (0.098)**

(*continued*)

Table 9 (*continued*)

Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Chronic conditions entering year *t*		
Heart/stroke	–0.119 (0.046)**	–0.103 (0.059)*
Respiratory	0.067 (0.061)	0.026 (0.079)
Cancer	0.064 (0.056)	0.061 (0.073)
Diabetes	0.109 (0.054)**	–0.250 (0.076)**
Medical care use last year *t-1*		
Any hospitalization	0.113 (0.062)*	0.110 (0.074)
Any physician service use	–1.149 (0.055)**	–0.938 (0.072)**
Any prescription drug use	1.258 (0.067)**	1.226 (0.085)**
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	12.954 (0.547)**
Loading ω on time-varying factor υ_t	—	–0.309 (0.136)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level. Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

are more likely to have supplemental insurance plans and are more likely to have prescription drug coverage. Similarly, they are more likely to experience health shocks of the kind we model. 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 in Section VB.

B. Simulations of Drug Coverage

1. Simulation Details

The effect of drug coverage on medical care demand and health outcomes 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 simulation 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 six different drug coverage scenarios supported by our estimated model. 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 (S_t) and demand for prescription drugs (D_t) and hospital and physician services (A_t, B_t) for the entire sample of 25,935 individuals given their initially observed characteristics. Supplemental health insurance (I_t, J_t) is not simulated because it is fixed as part of each policy simulation. The current period health

Table 10
Parameter Estimates for Selected Variables Explaining Prescription Drug Coverage

Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Part C Plan (relative to private plan)	1.079 (0.037)**	5.821 (0.094)**
Functional status entering year *t*		
Moderately disabled	0.071 (0.027)**	0.060 (0.046)**
Severely disabled	0.037 (0.043)	–0.096 (0.078)**
Chronic conditions entering year *t*		
Heart/stroke	0.025 (0.024)	–0.010 (0.045)
Respiratory	0.080 (0.032)**	0.190 (0.062)**
Cancer	–0.053 (0.028)*	–0.172 (0.054)**
Diabetes	0.006 (0.029)	–0.298 (0.059)**
Medical care use last year *t-1*		
Any hospitalization	–0.042 (0.031)	0.020 (0.053)
Any physician service use	–0.337 (0.040)**	–0.372 (0.069)**
Any prescription drug use	0.146 (0.040)**	0.125 (0.074)
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	8.204 (0.103)**
Loading ω on time-varying factor υ_t	—	–0.113 (0.108)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level. Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

shocks determine chronic condition status entering the next period (E_{t+1}). We use the simulated medical care input choices and simulated health shocks to determine end-of-period functional status (F_{t+1}). These simulated health outcomes are then transferred to the next period. Conditional on the updated health and previous simulated medical care use, expenditures and current health shocks are again simulated. Given these, we update chronic conditions and simulate functional status. 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 (for example, age, marital status, rural residency, identifying variables, etc.).[17] 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 (that is, prescription drug, hospital, and physician services) and health outcomes (that is, shocks and functional

17. 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 identifying variables based on the individual's last observed zip code, county, or state of residence.

Table 11
Parameter Estimates for Selected Variables Explaining Health Shocks

Selected variables	Single equation without unobserved heterogeneity	Multiple equations with unobserved heterogeneity
Shock: Heart/Stroke		
Functional status entering year *t*		
Moderately disabled	0.215 (0.026)**	0.221 (0.026)**
Severely disabled	0.305 (0.037)**	0.324 (0.038)**
Chronic conditions entering year *t*		
Heart/stroke	1.413 (0.024)**	1.412 (0.025)**
Respiratory	0.219 (0.029)**	0.220 (0.030)**
Cancer	0.038 (0.027)	0.025 (0.028)
Diabetes	0.365 (0.026)**	0.355 (0.027)**
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	0.344 (0.033)**
Loading ω on time-varying factor υ_t	—	1.000 —
Shock: Respiratory		
Functional status entering year *t*		
Moderately disabled	0.416 (0.051)**	0.441 (0.057)**
Severely disabled	0.527 (0.070)**	0.592 (0.078)**
Chronic conditions entering year *t*		
Heart/stroke	0.442 (0.048)**	0.498 (0.053)**
Respiratory	2.315 (0.046)**	2.559 (0.055)**
Cancer	0.109 (0.052)**	0.141 (0.059)**
Diabetes	–0.030 (0.054)	–0.016 (0.060)
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	0.092 (0.071)
Loading ω on time-varying factor υ_t	—	5.493 (0.239)**
Shock: Cancer		
Functional status entering year *t*		
Moderately disabled	0.200 (0.047)**	0.216 (0.049)**
Severely disabled	–0.089 (0.075)	–0.044 (0.077)
Chronic conditions entering year *t*		
Heart/stroke	0.114 (0.042)**	0.100 (0.044)**
Respiratory	0.083 (0.052)	0.086 (0.055)
Cancer	2.156 (0.041)**	2.199 (0.043)**
Diabetes	0.088 (0.050)*	0.095 (0.052)*
Unobserved heterogeneity		
Loading ρ on permanent factor μ	—	0.421 (0.060)**
Loading ω on time-varying factor υ_t	—	2.718 (0.138)**

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level. Additional explanatory variables include exogenous individual characteristics (Table 5), relevant identifying variables (Table 6), and year indicators.

status) 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 expenditures 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) with drug coverage from one of the six sources assigned to all individuals for each of the five simulated years.

We demonstrate the fit of our preferred model by comparing observed outcomes of the sample with model predictions using estimated model parameters and observed exogenous explanatory variables. In Appendix Table A7, we summarize observed outcomes *by year* and report predictions from our model simulation using the updated values of endogenous regressors. Figure 2 depicts how well our model (indicated by open circles) fits the observed MCBS mortality rate (indicated by solid circles). 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 Figure 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 4 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 (functional status and chronic conditions), stochastic health shocks, and unobserved heterogeneity.

2. *Effects of Drug Coverage on Drug Expenditures*

Our preferred dynamic model with unobserved heterogeneity suggests that drug coverage increases prescription drug expenditures over a five-year period by 6.7 to 26.5 percent depending on the source of coverage (top half of Table 12).[18] More specifically, dual coverage by Medicaid (which covers prescription drug costs) results in a 26.5 percent increase in drug expenditures. As moral hazard suggests, the greater coverage and/or better cost-sharing characteristics associated with the private and Part C plans without drug coverage lead to greater consumption of medical care (a 6.2 and 10.8 percent increase, respectively). Additionally, prescription drug coverage from a private supplemental plan increases drug expenditures by 22.7 percent ($5,439 vs. $4,434) and drug coverage in a Part C plan results in a 6.7 percent increase in drug expenditures ($4,939 vs. $4,627) compared to similar plans with no drug coverage. The static model without heterogeneity suggests a larger average range of the increase in drug expenditures from 9.0 to 36.2 percent. Recall that estimation of the static model does not account for 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.

3. *Effects of Drug Coverage on Other Expenditures*

In contrast to the substantial increase in drug expenditures, hospital expenditures increase by up to 12 percent over five years with private or Part C coverage, but

18. The expenditures are averaged over time and over survivors in each of the five years.

Table 12

Five-year Simulation of Medial Care Expenditures and Health Outcomes with Different Types of Supplemental Health Insurance Coverage

	Medicare only	Medicaid	Percent Δ	Private no Rx	Percent Δ	Private with Rx	Percent Δ	Part C no Rx	Percent Δ	Part C with Rx	Percent Δ
Medical care expenditures (total over five years)											
With unobserved heterogeneity											
Prescription drug	4,176	5,283	**26.51**	4,434	**6.18**	5,439	**30.24**	4,627	**10.80**	4,939	**18.27**
Hospital	11,306	10,628	**–6.00**	11,689	**3.39**	12,931	**14.37**	11,343	**0.33**	12,690	**12.24**
Physician service	6,026	8,024	**33.16**	8,407	**39.51**	8,808	**46.17**	3,951	**–34.43**	3,269	**–45.75**
Total medical care	21,508	23,935	**11.28**	24,530	**14.05**	27,178	**26.36**	19,921	**–7.38**	20,898	**–2.84**
Without unobserved heterogeneity											
Prescription drug	3,217	4,381	**36.18**	3,860	**19.99**	5,122	**59.22**	3,525	**9.57**	3,843	**19.46**
Hospital	12,557	13,663	**8.81**	13,649	**8.70**	13,708	**9.17**	10,746	**–14.42**	11,939	**–4.92**
Physician service	4,607	7,143	**55.05**	6,827	**48.19**	6,927	**50.36**	2,893	**–37.20**	2,322	**–49.60**
Total medical care	20,381	25,187	**23.58**	24,336	**19.41**	25,757	**26.38**	17,164	**–15.78**	18,104	**–11.17**
Health Outcomes (at end of five years)											
With unobserved heterogeneity											
Survival	73.54	76.28	**2.75**	74.56	**1.02**	75.10	**1.57**	72.71	**–0.82**	73.63	**0.09**
Not disabled	64.82	62.77	**–2.05**	63.38	**–1.44**	61.90	**–2.92**	64.09	**–1.68**	63.14	**–0.73**
Moderately disabled	26.22	27.33	**1.11**	26.90	**0.69**	27.63	**1.41**	26.79	**1.18**	27.40	**0.57**
Severely disabled	8.96	9.90	**0.93**	9.72	**0.75**	10.47	**1.51**	9.47	**0.50**	9.13	**0.16**
Without unobserved heterogeneity											
Survival	71.10	74.28	**3.18**	73.53	**2.43**	75.57	**4.47**	71.07	**–0.03**	70.44	**–0.66**
Not disabled	66.07	63.16	**–2.91**	64.07	**–2.00**	62.43	**–3.63**	65.50	**–0.57**	64.60	**–1.47**
Moderately disabled	25.47	27.02	**1.54**	26.50	**1.03**	27.47	**2.00**	26.01	**0.53**	26.58	**1.11**
Severely disabled	8.46	9.82	**1.36**	9.43	**0.97**	10.10	**1.64**	8.50	**0.04**	8.82	**0.36**

Note: Percent Δ refers to percentage change for expenditures and percentage point change for health outcomes from the base case of Medicare only.

actually decrease with Medicaid coverage. Physician service expenditures are 33.2 percent larger for those dually covered by Medicaid. This combination of increased expenditures on drugs and physician services and reduced hospital expenditures suggests that medical care positively influences health leading to less need for hospital care among Medicaid-covered beneficiaries. While supplemental coverage by a private plan without drug coverage increases physician services use substantially (by 39.5 percent), the addition of drug coverage among private plans increases physician services expenditures by only 4.8 percent. Participation in Part C plans without drug coverage greatly reduces physician service expenditures (by 34.4 percent), while such plans with drug coverage reduce this demand even more (by 17.3 percent).

These responses reflect both substitution and 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, coverage from private plans is associated with greater consumption of all services (for example, prescription drug use requires physician consultation and followup) whereas Part C insurance seeks to control medical care use. In total, expenditures increase by 11.3 percent with dual coverage by Medicaid and 26.4 percent with a private supplemental plan (compared to Medicare coverage only), but fall slightly (between 2.8 and 7.4 percent) when all individuals are covered by Medicare's Part C plans with or without drug benefits. The static model without heterogeneity predicts that changes in these expenditures would be over twice as large in some cases.

4. *Effects of Drug Coverage on Health Outcomes*

In the lower panel of Table 12, our preferred model indicates that prescription drug coverage from all sources leads to increases in survival probabilities relative to coverage by Medicare only (except for a slight reduction in survival for those with Part C without drug coverage). 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.

5. *Effects on Sole and Marginal Survivors*

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 Part C drug benefit is available. As expected, sole survivors are healthier in year one than marginal survivors (top panel of Table 13). 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

Table 13
Total (five-year) Expenditures of Sole Survivors vs. Marginal Survivors with Different Types of Supplemental Health Insurance Coverage

	Medicaid		Private with Rx		Part C with Rx	
	Marginal	Sole	Marginal	Sole	Marginal	Sole
Initial Condition						
Age	76.71	73.37	76.71	73.33	76.23	73.21
Male	0.44	0.40	0.43	0.40	0.45	0.40
Log income	9.67	9.83	9.66	9.83	9.69	9.84
Height	65.73	65.69	65.68	65.68	65.81	65.67
Moderately disabled	0.34	0.26	0.33	0.26	0.33	0.26
Severely disabled	0.12	0.06	0.12	0.06	0.11	0.06
Chronic condition: heart/stroke	0.53	0.42	0.52	0.42	0.54	0.42
Chronic condition: respiratory	0.17	0.13	0.16	0.13	0.18	0.13
Chronic condition: cancer	0.24	0.16	0.23	0.16	0.24	0.16
Chronic condition: diabetes	0.22	0.19	0.2	0.18	0.21	0.18
Medical care expenditures						
Prescription drug expenditures						
Medicare only	2,031	4,934	1,656	4,938	1,774	4,962
Plan with Rx coverage	6,359	6,093	6,557	6,313	6,424	5,823
Percent Δ	**213.10**	**23.49**	**295.95**	**27.85**	**262.12**	**17.35**
Hospital expenditures						
Medicare only	14,008	10,121	11,699	10,122	15,106	10,142
Plan with Rx coverage	16,057	9,264	18,952	11,482	21,184	11,692
Percent Δ	**14.63**	**–8.47**	**62.00**	**13.44**	**40.24**	**15.28**
Physician service expenditures						
Medicare only	4,566	6,443	3,686	6,417	5,003	6,394
Plan with Rx coverage	11,297	8,488	11,651	9,393	5,365	3,376
Percent Δ	**147.42**	**31.74**	**216.09**	**46.38**	**7.24**	**–47.20**
Total medical care expenditures						
Medicare only	20,605	21,498	17,041	21,477	21,883	21,498
Plan with Rx coverage	33,713	23,845	37,160	27,188	32,973	20,891
Percent Δ	**63.62**	**10.92**	**118.06**	**26.59**	**50.68**	**–2.82**

Note: Percent Δ refers to percentage change for expenditures and percentage point change or health outcomes from the base case of Medicare only.

sole survivors increase their drug consumption a moderate amount (≈22 percent), and experience a slight increase in hospital expenditures (≈1.5 percent) over five years. When dually covered by Medicaid, sole survivors spent 8.5 percent less on hospital expenditures than when covered by Medicare Parts A and B only. The marginal survivors, however, more than double their expenditures on drugs, and consume significantly more hospital services. Physician services use among those with Part C coverage actually drops for the sole survivors, with only a small increase in those expenditures for the marginal survivors relative to the large increases for marginal survivors with Medicaid or private coverage.

The effect of drug coverage on long-run behavior is also evident by examining changes in five-year expenditures in each service category conditional on whether the health of sole survivors improved, was maintained, or deteriorated. (Results available from authors by request.) While expenditures (generally) increase across insurance plans and type of medical care for each of these health transition categories, the percentage change in expenditures of individuals whose health deteriorated was 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 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 effect of omission of dynamic behavior from the effect of omission of unobserved heterogeniety. The bias eliminated by the modeling of unobserved heterogeneity is apparent in Table 14 by comparing results from the two different estimation procedures (*with and without unobserved heterogeneity*). The top panels of Table 12 and Table 14 demonstrate the effects of dynamic health outcomes and lagged expenditure behavior by comparing expenditures simulated over five years with (a five-year extrapolation of) simulated expenditures in one year.

IV. Summary

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 7 and 27 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 drugs and physician services, largely due to increased longevity. But, those with Medicaid coverage experience reduced hospital expenditures over the five-year simulation. Furthermore, individuals with Part C plans 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 medical care consumption of the elderly is correlated over time, and that this relationship depends on both permanent and time-varying observed and 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.

Table 14
One-year Simulation of Medial Care Expenditures and Health Outcomes with Different Types of Supplemental Health Insurance Coverage

	Medicare only	Medicaid	percent Δ	Private no Rx	percent Δ	Private with Rx	percent Δ	Part C no Rx	percent Δ	Part C with Rx	percent Δ
Medical care expenditures (total over one year)											
With unobserved heterogeneity											
Prescription drug	949	1,123	**18.34**	943	**–0.63**	1,138	**19.92**	1,026	**8.11**	1,026	**8.11**
Hospital	2,301	2,105	**–8.52**	2,360	**2.56**	2,585	**12.34**	2,258	**–1.87**	2,489	**8.17**
Physician service	1,457	1,817	**24.71**	1,874	**28.62**	1,941	**33.22**	994	**–31.78**	847	**–41.87**
Total medical care	4,707	5,045	**7.18**	5,177	**9.99**	5,664	**20.33**	4,278	**–9.11**	4,362	**–7.33**
Without unobserved heterogeneity											
Prescription drug	740	928	**25.41**	823	**11.22**	1,070	**44.59**	797	**7.70**	856	**15.68**
Hospital	2,892	3,057	**5.71**	3,100	**7.19**	3,053	**5.57**	2,380	**–17.70**	2,574	**–11.00**
Physician service	1,218	1,724	**41.54**	1,641	**34.73**	1,641	**34.73**	801	**–34.24**	665	**–45.40**
Total medical care	4,850	5,709	**17.71**	5,564	**14.72**	5,764	**18.85**	3,978	**–17.98**	4,095	**–15.57**
Health Outcomes (at end of one year)											
With unobserved heterogeneity											
Survival	94.41	94.50	**0.10**	94.50	**0.10**	94.58	**0.18**	94.40	**0.00**	94.43	**0.02**
Not disabled	60.45	60.59	**0.14**	60.59	**0.14**	60.57	**0.12**	60.28	**–0.17**	60.11	**–0.33**
Moderately disabled	29.40	29.26	**–0.14**	29.26	**–0.14**	29.24	**–0.16**	29.68	**0.27**	29.90	**0.50**
Severely disabled	10.15	10.15	**0.00**	10.15	**0.00**	10.19	**0.04**	10.05	**–0.11**	9.98	**–0.17**
Without unobserved heterogeneity											
Survival	95.72	95.77	**0.05**	95.74	**0.02**	95.80	**0.08**	95.74	**0.02**	95.75	**0.03**
Not disabled	60.09	60.29	**0.20**	60.28	**0.19**	60.29	**0.21**	59.92	**–0.16**	59.79	**–0.29**
Moderately disabled	29.78	29.51	**–0.27**	29.53	**–0.25**	29.50	**–0.28**	30.10	**0.32**	30.31	**0.52**
Severely disabled	10.13	10.20	**0.07**	10.19	**0.06**	10.20	**0.07**	9.97	**–0.16**	9.90	**–0.23**

Note: * percent Δ refers to percentage change for expenditures and percentage point change for health outcomes from the base case of Medicare only.

Returning to the general question of how health insurance affects medical care expenditures, our study vividly shows how health insurance for one type of medical care creates an additional change in medical care consumption 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 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.

Appendix

An individual n in our sample is followed for 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 III. 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 III.B. We use λ^r to indicate estimated parameters in the initial reduced-form equation $r, r = 1, \ldots, 5$. Parameter estimates for initial condition equations are found in Appendix Tables A2-A6.

We include four equations explaining existence of four chronic conditions, k: heart/stroke problems, respiratory problems, cancer, and diabetes. The probability of having ever had chronic condition k, relative to not having had it, is

$$\ln\left[\frac{\Pr(E_0^k = 1)}{\Pr(E_0^k = 0)}\right] = \lambda_0^{1k} + \lambda_1^{1k} X_t + \lambda_2^{1k} Z_0^H + \lambda_3^{1k} R_0 + \lambda_4^{1k} t + \rho^{1k} \mu$$
$$k = 1, 2, 3, \text{ and } 4.$$

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

$$\ln\left[\frac{\Pr(I_0 = i)}{\Pr(I_0 = 0)}\right] = \lambda_{0i}^2 + \lambda_{1i}^2 E_0 + \lambda_{2i}^2 X_0 + \lambda_{3i}^2 Z_0^I + \lambda_{4i}^2 R_0 + \lambda_{5i}^2 t + \rho_i^2 \mu$$
$$i = 1, 2, \text{ and } 3.$$

An indicator of drug benefits $(J_0 = 1)$ is modeled as a logit outcome for individuals with a private or Part C plan where

Table A1
Description of Dependent Variables in Initial Condition Equations

Notation	Variable name	Specification	Percent
E_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
I_0	Supplemental insurance in t=0	multinomial	
	Medicare only (no supplement)	logit	8.63
	Medicaid		11.53
	Private plan		64.90
	Part C plan		14.94
J_0	Prescription drug coverage in t=0 conditional on private or Part C plan	logit	61.83
$A_0 > 0$	Any hospitalization in t=0	logit	17.33
$B_0 > 0$	Any physician service use in t=0	logit	84.91
$D_0 > 0$	Any prescription drug use in t=0	logit	89.22
F_1	Functional status 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

Table A2
Parameter Estimates Explaining Initial Existing Chronic Conditions

Variable name	Heart/Stroke	Respiratory	Cancer	Diabetes
Age	0.053**	0.005	0.050**	0.011
	(0.007)	(0.010)	(0.009)	(0.009)
Age squared	–0.094**	–0.094**	–0.103**	–0.164**
	(0.023)	(0.035)	(0.029)	(0.032)
Male	0.051	0.076	–0.170**	0.211**
	(0.040)	(0.055)	(0.051)	(0.051)
Education	–0.012*	–0.037**	0.027**	–0.068**
	(0.006)	(0.009)	(0.008)	(0.008)
Race: black	0.117**	–0.182**	–0.139**	0.469**
	(0.045)	(0.064)	(0.059)	(0.051)
Race: Hispanic	–0.238**	–0.187	–0.263*	0.354**
	(0.099)	(0.136)	(0.139)	(0.108)
Race: other nonwhite	–0.229*	–0.088	–0.320*	0.214
	(0.126)	(0.174)	(0.177)	(0.145)
Log income	0.141**	0.125	–0.080	0.436**
	(0.059)	(0.077)	(0.071)	(0.083)
Log income squared	–0.135**	–0.148**	0.069*	–0.407**
	(0.034)	(0.046)	(0.041)	(0.049)
Marital status: widowed	0.062*	0.032	0.050	0.054
	(0.032)	(0.045)	(0.040)	(0.040)
Marital status: separated, divorced, single	0.065	0.155**	0.172**	–0.037
	(0.053)	(0.068)	(0.065)	(0.066)

(continued)

Table A2 (*continued*)

Variable name	Heart/Stroke	Respiratory	Cancer	Diabetes
Rural	0.201**	0.149**	0.000	0.000
	(0.030)	(0.041)	(0.038)	(0.038)
Smoke ever	0.191**	0.784**	0.129**	–0.068*
	(0.028)	(0.042)	(0.035)	(0.036)
Birth cohort	–0.041	–0.096	0.054	–0.033
	(0.043)	(0.060)	(0.054)	(0.055)
Initial height	0.018**	–0.011*	0.024**	0.006
	(0.005)	(0.007)	(0.006)	(0.006)
Mean air quality	–0.001	–0.003*	0.003**	0.000
	(0.001)	(0.002)	(0.002)	(0.002)
Calendar year	0.034**	0.012	–0.006	–0.022**
	(0.007)	(0.010)	(0.009)	(0.009)
Loading ρ on permanent factor μ	0.147**	–0.018	0.148**	1.000
	(0.039)	(0.055)	(0.048)	—

Note: Standard errors are in parentheses. ** indicates significance at the 5 percent level; * 10 percent level. The factor loading on permanent heterogeneity in the diabetes equation is normalized.

Table A3
Parameter Estimates Explaining Initial Supplemental Insurance

Variable name	Medicaid	Private Plan	Part C Plan	Drug coverage if private or part C plan
Part C supplemental plan	—	—	—	5.188**
	—	—	—	(0.108)
Chronic condition: heart/stroke	0.429**	0.095	–0.189**	–0.046
	(0.065)	(0.093)	(0.074)	(0.053)
Chronic condition: respiratory	0.539**	0.052	0.107	0.107
	(0.087)	(0.130)	(0.104)	(0.075)
Chronic condition: cancer	0.074	0.301**	0.058	–0.124*
	(0.085)	(0.117)	(0.096)	(0.065)
Chronic condition: diabetes	0.330**	–0.671**	–0.286**	–0.240**
	(0.077)**	(0.118)	(0.097)	(0.067)
Age	0.011	0.090**	0.053**	–0.040**
	(0.017)	(0.023)	(0.019)	(0.009)
Age squared	–0.038	–0.312**	–0.258**	—
	(0.051)	(0.073)	(0.062)	—
Male	–0.078	–1.109**	–0.445**	–0.161*
	(0.099)	(0.140)	(0.114)	(0.089)
Education	–0.099**	0.147**	0.088**	0.073**
	(0.013)	(0.018)	(0.015)	(0.012)
Race: black	–1.029**	–6.411**	–3.386**	–1.744**
	(0.120)	(0.197)	(0.174)	(0.095)
Race: Hispanic	0.087	–7.342**	–3.491**	–2.601***
	(0.211)	(0.387)	(0.305)	(0.221)
Race: other nonwhite	–0.420*	–3.876**	–2.335**	–1.292**
	(0.241)	(0.402)	(0.324)	(0.277)
Marital status: widowed	1.494**	–1.088**	–0.523**	–0.245*
	(0.201)	(0.144)	(0.131)	(0.126)

(*continued*)

Table A3 (*continued*)

Variable name	Medicaid	Private Plan	Part C Plan	Drug coverage if private or part C plan
Marital status: separated, divorced, single	–1.218**	1.119**	0.671**	0.291**
	(0.123)	(0.093)	(0.084)	(0.071)
Log income	0.132*	–0.334**	–0.240**	–0.129**
	(0.079)	(0.109)	(0.090)	(0.063)
Log income squared	0.326**	–1.192**	–0.535**	–0.128
	(0.110)*	(0.172)	(0.135)	(0.118)
Rural	0.055	–0.555**	–1.128**	–0.216**
	(0.080)	(0.120)	(0.105)	(0.068)
Birth cohort	0.128	–0.155	–0.014	–0.037
	(0.108)	(0.143)	(0.120)	(0.084)
Veteran	–1.010**	–0.057	–0.255**	0.207**
	(0.110)	(0.134)	(0.108)	(0.076)
Initial height	–0.048**	0.035**	0.005	–0.001
	(0.010)	(0.012)	(0.011)	(0.010)
HMO penetration	3.179**	–3.061**	4.568**	1.882**
	(0.297)	(0.401)	(0.322)	(0.244)
Calendar year	–0.064**	–0.034	0.114**	0.175**
	(0.017)	(0.023)	(0.019)	(0.014)
Loading ρ on permanent factor μ	5.221**	18.457**	9.705**	7.234**
	(0.347)	(0.459)	(0.471)	(0.122)

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

Table A4
Parameter Estimates Explaining Initial Medical Care Use

Variable name	Any prescription drug use	Any hospitalization	Any physician service use
Medicaid	0.823 (0.093)**	0.117 (0.078)	1.027 (0.087)**
Private plan without Rx coverage	0.772 (0.106)**	0.129 (0.093)	1.851 (0.110)**
Private plan with Rx coverage	1.046 (0.157)**	0.130 (0.130)	2.003 (0.154)**
Part C plan without Rx coverage	0.665 (0.145)**	0.167 (0.136)	–0.474 (0.114)**
Part C plan with Rx coverage	0.950 (0.100)**	–0.126 (0.092)	–0.890 (0.085)**
Chronic condition: heart/stroke	1.632 (0.056)**	1.360 (0.038)**	1.008 (0.045)**
Chronic condition: respiratory	1.066 (0.089)**	0.729 (0.042)**	0.472 (0.065)**
Chronic condition: cancer	0.675 (0.067)**	0.505 (0.040)**	0.517 (0.058)**
Chronic condition: diabetes	1.321 (0.083)**	0.342 (0.041)**	0.591 (0.059)**
Age	0.029 (0.010)**	0.029 (0.008)**	0.084 (0.009)**
Age squared	–0.070 (0.039)*	–0.041 (0.031)	–0.216 (0.038)**
Male	–0.593 (0.046)**	0.134 (0.039)**	–0.366 (0.044)**
Education	0.015 (0.011)	–0.005 (0.009)	0.012 (0.010)
Race: black	–0.015 (0.083)	–0.117 (0.069)*	0.012 (0.075)
Race: Hispanic	0.080 (0.173)	–0.085 (0.145)	0.086 (0.142)
Race: other nonwhite	–0.162 (0.187)	–0.160 (0.183)	–0.388 (0.167)**
Log income	0.082 (0.024)**	–0.048 (0.021)**	0.094 (0.023)**
Marital status: widowed	–0.053 (0.054)	0.146 (0.043)**	–0.093 (0.051)*
Marital status: separated, divorced, single	–0.230 (0.082)**	0.011 (0.074)	–0.362 (0.074)**
Rural	–0.148 (0.062)**	0.022 (0.051)	0.207 (0.064)**
AAPCC Part A rate	–0.009 (0.005)*	0.008 (0.004)*	–0.014 (0.005)**
AAPCC Part B rate	0.012 (0.007)	0.000 (0.006)	0.003 (0.006)
Average prescription drug retail price	–0.010 (0.007)	0.011 (0.005)**	0.008 (0.006)

(*continued*)

Table A4 (*continued*)

Variable name	Any prescription drug use	Any hospitalization	Any physician service use
Reside < 100 miles of Canada/Mexico	–0.055 (0.059)	–0.064 (0.048)	–0.052 (0.054)
Number of physicians/1,000 elderly	0.000 (0.002)	0.001 (0.002)	0.000 (0.002)
Number of hospitals/1,000 elderly	0.152 (0.147)	0.100 (0.120)	0.073 (0.155)
Number of hospital beds/1,000 elderly	–0.001 (0.001)	0.000 (0.001)	0.003 (0.001)*
Calendar year	0.077 (0.013)**	–0.018 (0.011)	–0.140 (0.012)**
Loading ρ on permanent factor μ	–0.001 (0.152)	–0.059 (0.116)	–0.577 (0.156)**

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

Table A5
Parameters Explaining Initial Functional Status (relative to no functional limitation)

Variable name	Severely disabled	Moderately disabled
Chronic condition: heart/stroke	1.074**	0.709**
	(0.050)	(0.031)
Chronic condition: respiratory	0.886**	0.750**
	(0.060)	(0.041)
Chronic condition: cancer	0.382**	0.284**
	(0.056)	(0.037)
Chronic condition: diabetes	0.667**	0.346**
	(0.054)	(0.038)
Age	0.093**	0.067**
	(0.009)	(0.006)
Male	–0.755**	–0.687**
	(0.076)	(0.049)
Education	–0.064**	–0.046**
	(0.011)	(0.007)
Race: black	0.418**	0.156**
	(0.074)	(0.053)
Race: Hispanic	0.092	0.109
	(0.174)	(0.114)
Race: other nonwhite	0.015	0.104
	(0.225)	(0.145)
Marital status: widowed	0.721**	0.155**
	(0.195)	(0.064)
Marital status: separated, divorced, single	–0.532**	–0.191**
	(0.108)	(0.039)
Log income	–0.063	0.031
	(0.058)	(0.037)
Log income squared	0.213**	0.076
	(0.094)	(0.062)
Rural	–0.021	0.070**
	(0.053)	(0.034)
Birth cohort	0.119**	0.133**
	(0.052)	(0.034)
Initial height	–0.106	0.046
	(0.080)	(0.052)
Initial height squared	–0.462**	–0.133**
	(0.043)	(0.032)
Smoke ever	0.352**	0.096**
	(0.034)	(0.026)
Mean air quality	–0.036**	–0.048**
	(0.013)	(0.009)
Loading ρ on permanent factor μ	–0.285**	–0.096**
	(0.069)	(0.044)

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

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 use	–0.075 (0.136)	2.474 (0.085)**
Prescription drug expenditures, if any	0.180 (0.041)**	0.876 (0.026)**
Any hospitalization	–0.233 (0.123)*	7.481 (0.203)**
Hospital expenditures, if any	0.002 (0.063)	2.803 (0.069)**
Any physician service use	–0.042 (0.121)	1.619 (0.094)**
Physician service expenditures, if any	–0.017 (0.054)	3.779 (0.029)**
Functional status equation		
Die	–0.321 (0.074)**	–1.464 (0.273)**
Severely disabled	–0.330 (0.058)**	–0.445 (0.223)**
Moderately disabled	–0.212 (0.036)**	–0.118 (0.122)
Supplemental insurance choice		
Medicaid	7.692 (0.415)**	0.850 (0.129)**
Private plan	24.590 (0.546)**	0.606 (0.173)**
Part C plan	12.954 (0.547)**	–0.309 (0.136)**
Prescription drug coverage (if private or Part C plan)	8.204 (0.103)**	–0.113 (0.108)
Health shock probabilities		
Heart/stroke	0.344 (0.033)**	1.000 —
Respiratory	0.092 (0.071)	5.493 (0.239)**
Cancer	0.421 (0.060)**	2.718 (0.138)**
Initial condition equations		
Medicaid	5.221 (0.347)**	
Private plan	18.457 (0.459)**	

(*continued*)

Table A6 (*continued*)

Factor loading estimates			Permanent (ρ)	Time-varying (ω)
Part C plan			9.705 (0.471)**	
Prescription drug coverage (if private or Part C plan)			7.234 (0.122)**	
Any prescription drug use			–0.001 (0.152)	
Any hospitalization			–0.060 (0.116)	
Any physician service use			–0.577 (0.156)**	
Severely disabled			–0.285 (0.068)**	
Moderately disabled			–0.096 (0.044)**	
Heart/stroke			0.147 (0.039)**	
Respiratory			–0.018 (0.054)	
Cancer			0.148 (0.048)**	
Diabetes			1.000 —	
Heterogeneity distribution	Transformed mass point	Transformed weight	Mass point parameter estimate	Weight parameter estimate
Permanent (μ)	0.000	0.237	—	0.528 (0.024)**
	0.419	0.403	–0.329 (0.019)**	0.416 (0.022)**
	1.000	0.360	—	—
Time-varying (υ_t)	0.000	0.122	—	1.620 (0.027)**
	0.636	0.615	0.556 (0.013)**	0.772 (0.048)**
	1.000	0.263	—	—

Table A7
Comparisons of Actual Observations and Model Predictions, by year

Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	Average
Medical care use probabilities and expenditures											
Prescription drug use											
Probability of any											
MCBS	0.87	0.87	0.87	0.88	0.88	0.90	0.91	0.91	0.92	0.92	0.90
Simulation	0.85	0.88	0.87	0.90	0.90	0.90	0.91	0.92	0.93	0.93	0.90
Expenditures, if any											
MCBS	846	711	754	781	828	896	1,023	1,142	1,283	1,435	969
Simulation	—	757	793	850	893	910	1,103	1,229	1,274	1,372	1,016
Hospitalization											
Probability of any											
MCBS	0.17	0.19	0.20	0.19	0.19	0.20	0.19	0.20	0.20	0.22	0.20
Simulation	0.15	0.18	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.22	0.19
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	—	11,901	12,334	12,979	12,884	12,834	13,421	13,903	12,809	13,706	12,936
Physician service use											
Probability of any											
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	0.88	0.87	0.88	0.86	0.83	0.80	0.80	0.82	0.85
Expenditures, if 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	—	1,752	1,844	1,890	2,011	1,972	2,260	2,297	2,250	2,486	2,167
Functional status probabilities											
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	0.29	0.28	0.28	0.27	0.27	0.26	0.26	0.26	0.27	0.27
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	0.10	0.10	0.10	0.09	0.09	0.08	0.08	0.09	0.09	0.09
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	0.04	0.04	0.03	0.03	0.03	0.03	0.02	0.03	0.04	0.03

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	0.11	0.09	0.10	0.09	0.08	0.08	0.09	0.09	0.10	0.10	0.09
Private plan											
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	0.69	0.69	0.68	0.67	0.64	0.62	0.61	0.62	0.66
Part C plan											
MCBS	0.08	0.10	0.11	0.14	0.15	0.17	0.19	0.20	0.20	0.19	0.15
Simulation	0.09	0.11	0.13	0.14	0.15	0.17	0.20	0.22	0.22	0.21	0.16
Prescription drug coverage (if private or part C plan)											
MCBS	0.45	0.51	0.51	0.61	0.63	0.66	0.68	0.72	0.72	0.74	0.63
Simulation	0.48	0.50	0.55	0.56	0.60	0.64	0.67	0.72	0.71	0.72	0.62

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.

$$\ln\left[\frac{\Pr(J_0=1|I_0=2\,\text{or}\,3)}{\Pr(J_0=0|I_0=2\,\text{or}\,3)}\right]=\lambda_0^3+\lambda_1^3 1[I_0=3]+\lambda_2^3E_0+\lambda_3^3X_0+\lambda_4^3Z_0^I+\lambda_5^3R_0+\lambda_6^3t+\rho^3\mu.$$

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

$$\ln\left[\frac{\Pr(q_0>0)}{\Pr(q_0=0)}\right]=\lambda_0^{4q}+\lambda_1^{4q}I_0J_0+\lambda_2^{4q}E_0+\lambda_3^{4q}X_0+\lambda_4^{4q}Z_0^M+\lambda_5^{4q}R_0+\lambda_6^{4q}t+\rho^{4q}\mu$$

$$q=A,B,\ \text{and}\ D.$$

There is no need to model expenditures conditional on any in the initial period. The levels of expenditures explain health production at the end of each period, but these expenditures are modeled each period. Finally, functional status entering period $t=1$ is a multinomial logit with the outcomes not disabled (no ADLs or IADLs), moderately disabled (at least one IADL limitation and up to two ADL limitations), and severely disabled (more than two ADL limitations) where

$$\ln\left[\frac{\Pr(F_1=f)}{\Pr(F_1=0)}\right]=\lambda_{0f}^5+\lambda_{1f}^5E_0+\lambda_{2f}^5X_0+\lambda_{3f}^5R_0+\lambda_{4f}^5t+\rho_f^5\mu$$

$$f=1\ \text{and}\ 2.$$

All equations contain exogenous variables (R_0) that are excluded from the subsequent dynamic equations in $t=1,\ldots,T$. The additional identifying 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 each other and 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), child care (Blau and Hagy 1998), and disability insurance (Kreider and Riphahn 2000). 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, ν_{lt}, and the probability weights, φ_l, $l=1,\ldots,L$, are estimated (with the appropriate normalizations for identification).[19] This approach models the common heterogeneity that affects health insurance, medical care 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

19. We do not estimate the number of mass points, M and L, nonparametrically. 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.

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

$$
\begin{aligned}
L(\Theta) = \prod_{n=1}^{N} \Bigg\{ & \sum_{m=1}^{M} \theta_m \prod_{k=1}^{K} (\Pr(E_0^k = 0 \mid \mu_m)^{1(E_{n0}^k=0)} \cdot \Pr(E_0^k = 1 \mid \mu_m)^{1(E_{n0}^k=1)}) \\
& \cdot \prod_{i=0}^{3} \Pr(I_0 = i \mid \mu_m)^{1(I_{n0}=i)} (\prod_{j=0}^{1} \Pr(J_0 = j \mid \mu_m)^{1(J_{n0}=j)})^{1(I_{n0}=2,3)} \\
& \cdot \Pr(A_0 = 0 \mid \mu_m)^{1(A_{n0}=0)} [1-\Pr(A_0 > 0 \mid \mu_m)^{1(A_{n0}>0)} \\
& \cdot \Pr(B_0 = 0 \mid \mu_m)^{1(B_{n0}=0)} [1-\Pr(B_0 > 0 \mid \mu_m)^{1(B_{n0}>0)} \\
& \cdot \Pr(D_0 = 0 \mid \mu_m)^{1(D_{n0}=0)} [1-\Pr(D_0 > 0 | \mu_m)^{1(D_{n0}>0)} \\
& \cdot \prod_{f=0}^{2} \Pr(F_1 = f \mid \mu_m)^{1(F_{n1}=f)} \\
& \prod_{t=1}^{T} \Bigg[\sum_{l=1}^{L} \psi_l \prod_{i=0}^{3} \Pr(I_t = i \mid \mu_m, \upsilon_{lt})^{1(I_{nt}=i)} (\prod_{j=0}^{1} \Pr(J_t = j \mid \mu_m, \upsilon_{lt})^{1(J_{nt}=j)})^{1(I_{nt}=2,3)} \\
& \cdot \prod_{k=1}^{3} \Pr(S_t^k = 0 \mid \mu_m, \upsilon_{lt})^{1(S_{nt}^k=0)} \Pr(S_t^k = 1 \mid \mu_m, \upsilon_{lt})^{1(S_{nt}^k=1)} \\
& \cdot \Pr(A_t = 0 \mid \mu_m, \upsilon_{lt})^{1(A_{nt}=0)} [1-\Pr(A_t > 0 \mid \mu_m, \upsilon_{lt}) \cdot \phi_A(\cdot \mid \mu_m, \upsilon_{lt})]^{1(A_{nt}>0)} \\
& \cdot \Pr(B_t = 0 \mid \mu_m, \upsilon_{lt})^{1(B_{nt}=0)} [1-\Pr(B_t > 0 \mid \mu_m, \upsilon_{lt}) \cdot \phi_B(\cdot \mid \mu_m, \upsilon_{lt})]^{1(B_{nt}>0)} \\
& \cdot \Pr(D_t = 0 \mid \mu_m, \upsilon_{lt})^{1(D_{nt}=0)} [1-\Pr(D_t > 0 \mid \mu_m, \upsilon_{lt}) \cdot \phi_D(\cdot \mid \mu_m, \upsilon_{lt})]^{1(D_{nt}>0)} \\
& \cdot \prod_{f=0}^{3} \Pr(F_{t+1} = f \mid \mu_m, \upsilon_{lt})^{1(F_{nt+1}=f)} \Bigg] \Bigg\}.
\end{aligned}
$$

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.

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