THE IMPACT OF IMPERFECT INFORMATION ON THE HEALTH INSURANCE CHOICE, HEALTH OUTCOMES AND MEDICAL EXPENDITURES OF THE ELDERLY

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ABSTRACT

PRAGYA SINGH : The Impact of Imperfect Information on the Health Insurance Choice, Health Outcomes and Medical Expenditures of the Elderly
(Under the direction of Donna Gilleskie)

Traditional choice models assume that individuals have full information about the set of available products and their characteristics. However, recent empirical studies illustrate the importance of limited information about product availability and characteristics in consumer decision making. The market for health insurance is an important market in which the inherent product complexity frequently leads to incomplete consideration or attention to plan alternatives and their features. This research investigates the dynamic impact of limited information about the insurance alternatives available through Medicare on the expenditures and health outcomes of the elderly, using the Medicare Current Beneficiary Survey (MCBS) dataset, which reports individuals' knowledge about insurance plan characteristics as well as their choice of plan. Simulations from parameter estimates obtained through joint estimation of demand equations show that more informed individuals are more likely to supplement traditional fee-for-service Medicare with Prescription Drug coverage and other supplemental insurance policies and, in spite of consuming more medical care, realize lower out-of-pocket expenditures. Increasing the value of the information measure used in this study by one standard deviation, produces a 30 dollar decrease in out-of-pocket expenditures per beneficiary. However, the total medical care expenditure for each Medicare beneficiary increases by 432 dollars. This net increase in spending of 402 dollars per beneficiary has to be weighed against a positive impact on health status of elderly persons with functional limitations. The probability of such individuals transitioning into a 'no functional limitation' state increases by 2 per cent with the increase in information. Furthermore, with limited resources available to

expand insurance literacy, policymakers should target the elderly in lower health status for they realize lower out-of-pocket expenditures as well as an improvement in their health outcomes.

To my parents:
for the many sacrifices that they made in their unflinching commitment to provide me the best possible education,
for always pushing me to realize my potential,
and for instilling in me the determination and perseverance needed to get here

AND

To my husband:
for being himself

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CHAPTER 1

INTRODUCTION

Frankie Huff is working on her doctoral degree in Florida and can tackle the most complicated education theories with ease. That's not the case when it comes to picking a health insurance plan through her school. "It is daunting–at times more difficult to interpret than the scholarly research I pore through for my own dissertation," she says.

This excerpt from CNN Health illustrates the challenge that millions of Americans face every open enrollment season − understanding their health insurance coverage options, comparing them on various dimensions, and making an optimal choice. Recent survey data (Handel and Kolstad, 2013) and empirical research (Bhargava et al., 2015; Lin and Wildenbeest, 2013) show that there are considerable information frictions in the market for health insurance; consumers often do not consider all the options available to them, fail to give attention to individualized plan characteristics, and consequently,do not select the best option.

These aspects of consumer behavior may be explained in terms of costs of acquiring information, where costs are defined very broadly and include pecuniary costs of acquiring information such as access to a personal computer or internet, time costs or cognitive costs of processing information. As a consequence of these information constraints, consumers frequently end up having incomplete and incorrect information about coverage options and plan features.[1]

Individuals with limited information on insurance alternatives and the characteristics of those

[1]Data from the 2009 Medicare Current Beneficiary Survey (used in this study) indicate alarmingly low levels of information among Medicare beneficiaries about the options available to them. For instance, 35 per cent of respondents reported not being sure if there are any coverage options available with Medicare and nearly half of all respondents incorrectly believe that out-of-pocket costs are the same for all Prescription Drug Plans available through Part D of Medicare.

alternatives may be making suboptimal plan choices, not getting the coverage that they need, getting it at higher costs, or potentially over insuring themselves. Since subsequent medical care utilization depends on the marginal effective prices[2] of medical care induced by the chosen plan and medical care inputs improve, maintain or reduce deterioration of health, limited information indirectly affects health outcomes. For instance, use of preventive care services, (e.g., mammogram, prostate and cancer screenings) can lead to early detection of health conditions, thus slowing or reversing deterioration of untreated health in the future. Uncertainty about the coverage of these services[3] is likely to impact utilization of these services, thus affecting long term individual health.

Grossman (1972) initiated the conceptualization of health as a capital good (i.e., it lasts, may depreciate, and can be augmented through investment). Thus, the effects of imperfect information today may have implications for future health outcomes; that is, limited information has dynamic (and long-run) consequences, rather than simply static (short-run) ones.

The level of information possessed by an individual is not randomly distributed. Many observed and unobserved characteristics of the individual (e.g., education, health status, risk aversion) and her community (e.g., internet access, public libraries, information campaigns) determine how much information she seeks and how well that information is processed. Hence, there may be selection into obtaining more information. The causal impact of imperfect information on individual choices and outcomes cannot be measured without taking into account this potential endogeneity.

The broad objective of this research is to examine the dynamic causal impacts of limited information on the choices of insurance and medical care consumption, medical care expenditures and health outcomes of the elderly. To this end, the paper exploits some unique features of the Medicare Current Beneficiary Survey (MCBS) conducted by the Centers for Medicare and Medicaid Services (CMS) to identify the extent of information possessed by the beneficiaries. The MCBS is a longitudinal survey of Medicare beneficiaries that is linked to Medicare claims data and provides

[2]Marginal effective prices are determined by features such as deductible, coinsurance and out-of-pocket maximum of the plan.

[3]A quarter of female respondents in the 2009 MCBS are not aware that Medicare covers an annual mammogram.

a complete picture of the utilization and expenditures of the beneficiaries as well as their health conditions and insurance choices each period. One component of the survey data files is the Beneficiary Needs and Knowledge Supplement, which is designed as a quiz testing the knowledge of beneficiaries on various aspects of coverage alternatives and the services covered under Medicare. In this research, the number of correct responses to these questions provided by the beneficiary is used as a measure of her information.

The impact of information is analyzed in the context of a dynamic decision making model in which agents make sequential decisions about information seeking, insurance selection, and preventive and curative medical care consumption. The theoretical framework of the model is used to derive specifications of the demand equations for individual choices and stochastic evolution of medical expenditures and health outcomes. These dynamic equations are estimated jointly along with the distributions of unobserved heterogeneity that allow for correlation across equations and over time using maximum likelihood estimation. Theoretically-relevant exogenous variables are used as exclusion restrictions for identification, which is also aided by the use of panel data and functional form restrictions in the estimation equations.

Parameter estimates from the model reveal that imperfect information is significant in explaining health insurance choices and medical care use and expenditures. Better informed individuals are more likely to choose Medicare Advantage plans or supplement the fee-for-service (FFS) Medicare with Part D coverage and other supplemental insurance policies such as Medigap. The average utilization of preventive care services, outpatient care, and prescription drugs increases with information leading to higher total expenditures. Out-of-pocket expenditures, however, decline with greater information. Using the parameter estimates, simulation of individual choices and outcomes under the scenario when all individuals have full information (i.e., answer all questions correctly) versus when they have no information shows an 8.5 per cent decline in out-of-pocket expenditures. The probability of continuing to be in lower health status (measured by functional limitations) declines by approximately 11 per cent with greater information. The effect of having a personal computer at home and receiving the ‘Medicare and You’ book (which provides details on insurance choices) has a positive significant impact on information, and policies that provide greater access to such resources are predicted to increase average information in the population.

Survey data on how consumers make insurance choices or how well informed they are while selecting insurance are not commonly available.[4] As such, empirical research in information frictions in the health insurance market has generally focused on identifying friction hypotheses about consumer behavior from individual insurance choices and exogenous variations in choice environment and examining the welfare effects of these information frictions on insurance costs or annual out-of-pocket expenditures, taking medical care consumption as exogenous.[5] Thus, information has no effects on medical care consumption or health in these models. This research contributes to the existing literature on health insurance choice and medical care use in several distinct ways. To the best of my knowledge, this is the first study to 1) use survey data on information possessed by individuals while making choices and also model the potential endogeneity of this information in order to 2) examine the causal impact of imperfect information on insurance selection as well as subsequent medical care utilization and expenditures thus 3) allowing for dynamic effects of imperfect information through its impact on health outcomes. An additional advantage of modeling the choice of medical care utilization is that I can identify effects of information on total medical expenditures distinctly from its impact on individual out-of-pocket expenditures.

The dissertation proceeds as follows: Chapter 2 provides a survey of the relevant literature. Chapter 3 gives a brief overview of the Medicare program. Theoretical motivation and the empirical framework are provided in Chapter 4. Chapter 5 discusses the estimation strategy and identification. The longitudinal data are described in Chapter 6. Discussion of results, parameter estimates and policy simulations follows in Chapter 7 and Chapter 8 summarizes the findings.

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[4] Handel and Kolstad (2013) is the only other study using survey data that include information levels of participants.

[5] For example, Lin and Wildenbeest (2013) explore search costs, Handel (2013) explore switching costs, and Ho et al. (2015) explore inattention. These studies also typically capture general equilibrium effects incorporating these frictions in insurer pricing strategies. The present paper does not examine such pricing effects.

CHAPTER 2

LITERATURE REVIEW

Recent empirical studies have documented suboptimal insurance choices in the health insurance market in United States. Abaluck and Gruber (2011) use detailed Medicare Part D Prescription Drug Plan claims and plan choice data to show that choices of the majority of Medicare population are not consistent with optimization under full information. Instead, an alternative plan in the individual's choice set frequently offers better risk protection at a lower cost. Such inefficient choices are not confined to the elderly. Bhargava et al. (2015) examine health insurance decisions of employees at a large U.S. firm and find that a significant fraction of employees choose financially dominated options, resulting in excess spending. They conclude that these choices reflect a severe deficit in health insurance literacy. Handel and Kolstad (2013) collect survey data from employees at a large firm testing their knowledge of the available insurance options and find considerable gaps in consumers' knowledge.[1] These information gaps matter for the insurance choices observed in their data.

Several sources of information frictions that could lead to inefficient plan choices have been identified in the literature. One explanation focuses on the presence of 'search costs', i.e., consumers have to pay a fixed cost[2] each time they examine another insurance plan and hence they end up considering only a subset of the alternatives. Lin and Wildenbeest (2013) find evidence for substantial search costs in the market for Medigap (supplemental) insurance policies. Another consumer behavior that has been explored is 'inertia' or 'switching costs'. Strombom et al. (2002) find that price sensitivity in health plans is negatively correlated with age, job tenure and health risk

[1]The Beneficiary Needs and Knowledge Supplement component of the MCBS used in the paper has a similar structure.

[2]This fixed cost can be thought of as the opportunity cost of time.

variables that they interpret to be proxies for switching costs. Handel (2013) uses proprietary data on health plan choices and medical utilization of employees and finds large estimates of switching costs. Reducing these costs is beneficial for consumer welfare in a partial equilibrium framework, but the same policy exacerbates adverse selection and reduces consumer welfare when insurer pricing strategies are taken into account. Nosal (2012) uses the three level nested fixed point estimation routine of Gowrisankaran and Rysman (2009) to estimate switching costs for Medicare Advantage (MA) Plans with market share data and finds that the percentage of consumers opting for Medicare Advantage over FFS Medicare would more than triple in the absence of switching costs. Consumer inattention is also posited as an explanation for inefficient choices in the literature. Ho et al. (2015) estimate a model of consumer choice with inattentive consumers and explore the implications of inattention for insurer pricing. In their model, consumers actively find information about their insurance choice set only when they are hit by a sufficiently large shock to their plan costs or health in the last period. Their results show considerable consumer savings through reduced premiums when inattention is removed.

In these studies of information frictions, medical care utilization is commonly assumed to be exogenous, i.e., demand for medical care does not change with insurance. However, the choice of health insurance affects the subsequent medical care utilization through its impact on the effective prices of medical care, and both these decisions are affected by correlated unobserved factors. Since medical care is an investment in the production of health, insurance choice also indirectly affects health outcomes.

Several studies have examined the responsiveness of medical care utilization to insurance coverage and its impact on health with varying results. One of the earliest studies in this context is the Rand Health Insurance Experiment (HIE) (Manning et al., 1987). This study randomly assigned health insurance plans to participants and recorded their medical care consumption and health outcomes over the next three to five years. The individuals in plans that had cost sharing consumed less medical care than those who had free plans with no cost sharing. The reduction in services had no adverse effect on participants' health in general. However, the poorest and the sickest had better outcomes with a free plan. A more recent experimental study is the 2008 Oregon HIE , which expanded the state's Medicaid program to 10,000 additional low income adults using a lottery (Finkelstein et al., 2011). The study finds an increase in medical care utilization and reduction in financial strain due to the expansion but no significant effects on health within a one year follow-up period. There are also many quasi-experimental studies that use potentially exogenous shifts in insurance policy to control for insurance selection. For example, Currie and Gruber (1996) and Dafny and Gruber (2005) use an expansion of Medicaid and Kolstad and Kowalski (2012) use the Massachusetts market reforms. Due to the investment good nature of health, effects of insurance selection are dynamic. A few studies examine this dynamic, long-term impact of insurance on individual health outcomes using longitudinal data. Yang et al. (2009) model Medicare beneficiaries' decisions to get supplemental insurance coverage for prescription drugs (prior to the introduction of Prescription Drug Coverage through Medicare Part D in 2006) in a framework where health evolves according to a production function (Grossman, 1972). They find that prescription drug coverage increases expenditures on drugs and reduces mortality rates, but the survivors have poorer health and higher total medical expenditures.

The studies analyzing the relationships between insurance selection, medical care utilization and health, however, bypass issues of information frictions in consumer insurance choice and assume decision-making under perfect information. By examining the impact of imperfect information on insurance choices, which are allowed to impact subsequent medical care utilization and evolution of health outcomes in a dynamic model, my research extends and contributes to both the literature on information frictions in insurance choice and the literature examining effects of insurance selection on medical care utilization and health.

CHAPTER 3

AN OVERVIEW OF THE MEDICARE PROGRAM

Medicare is a national social insurance program, administered by the U.S. federal government since 1966, that guarantees access to health insurance for Americans aged 65 and older who have worked and paid into the social security system. Younger people with disabilities as well as people with end stage renal disease are also eligible under varying criteria.

Medicare initially had two parts: Medicare Part A and Medicare Part B. Part A covers inpatient hospital stays and Part B helps pay for physician services not covered by Part A. Most Medicare beneficiaries do not pay a monthly Part A premium because they have had 40 or more 3 month quarters in which they paid Federal Insurance Contributions Act taxes; monthly premium payments are required for Part B. The Original Medicare was administered as a fee-for-service (FFS) program (with no restriction on hospital or doctor networks from participating Medicare providers) with a copayment rate (generally 20 per cent) and no cap on out-of-pocket expenditures. FFS Medicare beneficiaries can buy supplemental insurance, which helps with the out-of-pocket costs and other gaps in Parts A and B. This supplemental insurance may or may not cover prescription drugs.

In 2003, Medicare enabled beneficiaries to choose to receive their Medicare benefits from Part C plans (also referred to as Medicare Advantage (MA) plans), which can be purchased from private insurance companies. Part C plans are required to offer coverage that meets or exceeds the standards set by Medicare and has a cap on out-of-pocket expenditures. Unlike original Medicare, these plans generally restrict access to in-network doctors and hospitals. MA plans usually cover more services (e.g., dental care, vision care etc.) than original Medicare . Some MA plans cover prescription drugs also. While plans do not require any extra premium payments per se (other than the Part B premium), Medicare beneficiaries may have to pay an extra premium amount for other

MA services in some plans.

Medicare Part D came into effect in 2006. In order to receive this benefit, beneficiaries must enroll in a stand-alone Prescription Drug Plan (PDP) or a Medicare Advantage plan with prescription drug coverage (MA-PD). Prescription Drug Plans are offered by private insurance companies (and subsidized by Medicare) who are free to choose which drugs they wish to cover and at what tier they cover it. These plans usually have a premium, deductible and a copayment rate. Enrollment in Part D is generally voluntary, however, some people who receive assistance under certain federal programs are required to enroll.

The insurance choice set (I) of an individual obtaining their coverage through Medicare consists of the eight possible combinations of FFS Medicare, Medicare Advantage, PDP and Supplemental Insurance ($I \equiv [I^1, I^2, I^3, I^4, I^5, I^6, I^7, I^8]$) as shown in Table 3.1.

Table 3.1: Insurance Plan Choices

Plan	FFS Medicare	Medicare Adv.	PDP	Supp. Ins.
I^1	$\surd$			
I^2	$\surd$		$\surd$	
I^3	$\surd$			$\surd$
I^4	$\surd$		$\surd$	$\surd$
I^5		$\surd$		
I^6		$\surd$	$\surd$	
I^7		$\surd$		$\surd$
I^8		$\surd$	$\surd$	$\surd$

CHAPTER 4

MODEL

4.1 Theoretical Motivation

Grossman (1972) provides a theoretical framework for analyzing the demand for medical care that can be derived from the impact of medical care inputs on individuals' health. Since insurance determines the effective marginal prices of medical care services, the indirect utility of insurance is derived from its effect on the demand for medical care and health. Information about insurance alternatives helps individuals make better (more efficient) insurance plan choices. I adapt the Grossman approach to analyze the forward looking insurance and medical care decisions of the elderly as well as their demand for information.

Individuals in the model derive utility from consumption (C_t) and health (H_t), where per-period utility is $U_t = U(C_t, H_t)$. Health is influenced by a stochastic 'health shock' (S_t) (e.g., development of a chronic condition) and by curative medical care inputs (M_t) (e.g., hospital services, physician services, prescription drugs) which may augment the natural depreciation of the health stock over time or the negative impact of the stochastic shock. Additionally, preventive care medical inputs (F_t) (e.g., screenings for cancer, diabetes) can enable detection of health conditions in their early stages, thus preventing greater deterioration of health in the future. Non-medical care inputs such as nutrition, exercise, abstinence from risky behaviors (such as smoking) also affect health, although they are not modeled in this study due to lack of data on these health behaviors. If X_t represents demographic characteristics such as age and education, and we discretize health into $h = 1, \ldots H$ categories, then:

$$\Pr(H_{t+1} = h) = f^h(H_t, X_t, F_t, S_t, M_t), \quad h = 1, ..., H$$

and the probability of experiencing a health shock is written as:

$$\Pr(S_t = 1) = g^S(H_t, X_t, F_t)$$

The out-of-pocket price of medical care faced by the individual is determined by whether the medical care services are covered under the chosen insurance plan and, if covered, by the specific cost-sharing structure of the plan in terms of deductibles, coinsurance rate, copayments, and limits on maximum out-of-pocket expenditures. Through its impact on the out-of-pocket price, the insurance plan choice also affects an individual's utilization of medical care, thus affecting her health. These price and quantity (utilization) effects determine the individual's out-of-pocket expenditures and total expenditures on medical care.[1] Consumption, C_t, (on goods other than medical care) is the difference between the individual's income and the amount spent on premiums and out-of-pocket medical expenditures. The budget constraint of the individual is represented by:

$$Y_t = C_t + \mathbf{P}_t^I.(I_t, F_t, M_t)$$

where Y_t is income , C_t is a composite consumption good with price normalized to 1 and $\mathbf{P}_t^I \equiv (P_t^I, P_t^{FI}, P_t^{MI})$. P_t^I is the premium of insurance of plan I and (P_t^{FI}, P_t^{MI}) denote the actual effective price of preventive and curative medical services, respectively, when insurance plan I is chosen in period t.

Each period, prior to the realization of uncertain health shocks (S_t), health insurance (I_t) is selected. Medical care inputs (M_t, F_t) are then chosen and then health (H_{t+1}) evolves stochastically. Thus, each period, conditional on her information about the insurance choice set, the individual chooses among the coverage alternatives and levels of medical care utilization to maximize her remaining lifetime utility subject to per period budget constraints, the probability of realizing health shocks, and the uncertain health production process. When individuals have imperfect information

[1] Total expenditures refer to the total costs borne by the insurance provider and the individual.

about the features of their insurance alternatives, the price structure, ($\mathbf{P}_t^I \equiv (P_t^I, P_t^{FI}, P_t^{MI})$) under a specific plan, as perceived by the individual, can be different from the actual prices and budget constraint imposed by the plan, thus leading to 'mistakes' in insurance selection (i.e., choice of a plan which is different from the lifetime utility maximizing plan under perfect information). A theoretical model detailing the impact of imperfect information on individual welfare and the process of acquisition of costly information is provided in section A.1 of the Appendix.

A common assumption in models of information frictions is that once a product is chosen, its attributes are automatically revealed to agents. It is difficult to extend this assumption to health insurance plan choice. Uncertain features of the chosen insurance plan are frequently revealed to consumers either after the consumption of medical care or while the decision to consume care is being made. Hence, I allow imperfect information about the chosen insurance plan to persist during the period. This allows information to have direct effects on medical care consumption and expenditures in addition to the indirect effects through choice of insurance plan. For example, uncertainty about coverage of preventive care medical services could lead to under-utilization of these services thus negatively impacting long term health outcomes.[2] In other words, information could change the mix of medical care consumption chosen by individuals; informed individuals are more likely to consume preventive care services and other forms of discretionary care (such as regular follow-ups with their physicians) which could reduce their hospitalizations and more intensive care episodes in the future.

The utility loss due to suboptimal insurance plan choices or consumption of an inefficient mix of medical care services (or equivalently, the benefit of greater information), is likely to be higher for individuals in poorer health status who are expecting higher medical consumption in the period. The costs of acquiring information will also vary among individuals depending on access to information technology (e.g., internet, personal computer), public information campaigns, and

[2]The utilization of preventive care services is largely discretionary and most of these services are covered under Medicare. However, around 21 per cent of males in the 2009 MCBS are either not aware that screening for prostate cancer is covered under Medicare (for all insurance choices) or are unsure about it, potentially leading to under-utilization of these services.

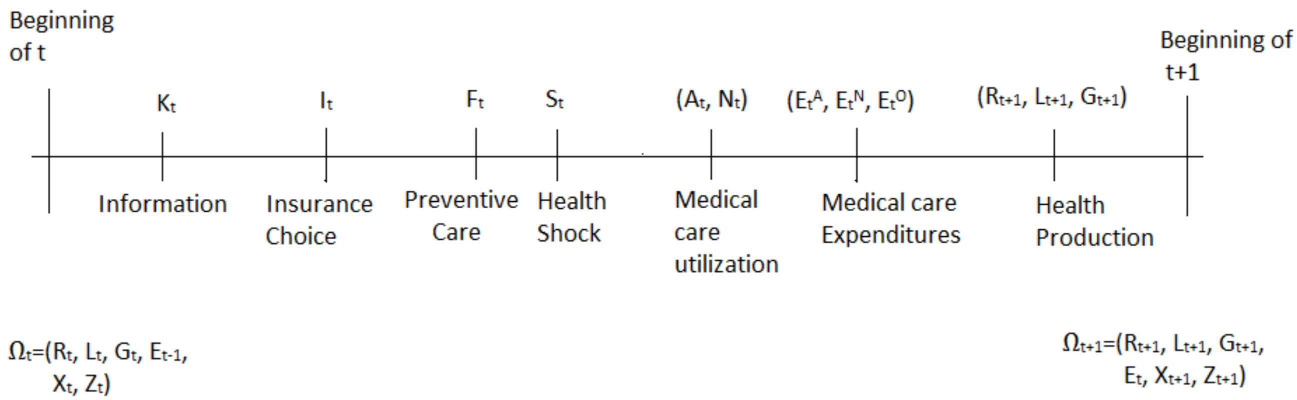

Figure 4.1: Timing of Annual Decisions, Health Shocks and Health Production

cognitive skills. Thus, the demand for information of a forward-looking individual will depend on the benefits and costs of greater information.

Figure 4.1 depicts the timing of annual information seeking, insurance and medical care decisions, health shocks, and health production that characterize the empirical model of individual behavior. At the beginning of the year, an elderly person collects information about her insurance alternatives (K_t) and makes a choice of insurance plan (I_t) for the year.[3] After selecting her insurance plan, she could choose to utilize preventive care medical services (F_t) such as screenings or flu shots. Afterwards, the individual may or may not experience a health shock (S_t). This health shock along with the existing health conditions of the individual coming into the year and her insurance coverage affect curative medical care consumption ($M_t \equiv (A_t, N_t)$) during the year. I model two categories of medical care: the first category is inpatient events (A_t), such as hospitalizations, which are covered under Part A, and the second category is outpatient (such as

[3]K_t represents information about the features of the individuals' insurance alternatives such as premiums, coverage, and deductibles. I acknowledge that information may not be available or perfect about other aspects of medical care decision making and the evolution of health. For example, individuals may not be aware of their metabolism rate or their genetic proclivity to obesity. I do not include such uncertainties and information problems as 1) their inclusion would make the model intractable and 2) data on the individuals' knowledge about these other aspects is not available.

physician visits) and prescription drug events (N_t) which are covered under Parts B and D, respectively.[4] The utilization of preventive and curative medical services along with the prices of medical care in the beneficiary's region and her insurance coverage together determine the expenditures ($E_t \equiv [E_t^A, E_t^N, E_t^O]$), where E_t^A is the total expenditure (incurred by the provider and the individual) on inpatient services, E_t^N is the total expenditure on outpatient services and drugs[5] and E_t^O is the out-of-pocket expenditure of the individual. At the end of the year, the health production process, which depends on health shocks and medical care inputs during the year, determines health next year ($H_{t+1} \equiv [R_{t+1}, L_{t+1}, G_{t+1}]$), measured by the number of severity adjusted chronic conditions (R_{t+1}), functional status (L_{t+1}) and self-reported health (G_{t+1}).

The information available to the individual at the beginning of each year is denoted by $\Omega_t = (R_t, L_t, G_t, E_{t-1}, X_t, Z_t)$. This information set includes observed health at the beginning of the period summarized by the number of severity adjusted chronic conditions (R_t), functional status (L_t) and self-reported health (G_t) entering period t. E_{t-1} is the total medical expenditure on medical care services (i.e., $E_{t-1} = E_{t-1}^A + E_{t-1}^N$) in the last period. Higher than expected expenditures in a period could prompt individuals to seek more information in the next period. Therefore, I allow lagged total medical care expenditure to influence individuals' information as well as insurance selection directly apart from its indirect effect through health. Information entering the period also includes exogenous individual characteristics (X_t) such as education, income, and age, exogenous theoretically-relevant variables reflecting price and supply conditions for insurance, and preventive and curative medical care ($Z_t^{\mathcal{I}}, Z_t^F,\ Z_t^M$) and exogenous shifters of information and health (Z_t^K, Z_t^H). The individual also knows all the current and lagged values of the permanent and time-specific components of the optimization problem that are unobserved by the researcher.

[4]Consumption of outpatient services and drugs is relatively more discretionary than consumption of inpatient services which are, quite frequently, urgent and non-discretionary. The effects of insurance coverage and information is likely to differ across these two categories of curative care.

[5]Preventive care services are outpatient events and hence expenditures on preventive care services are part of E_t^N.

4.2 Empirical Specification of Jointly Estimated Equations

1. *Information*

The expected value of being more informed about the insurance choice set depends on the individual's expectation of her medical care needs (i.e., her health during the period: R_t, L_t, G_t) , exogenous individual characteristics such as age, education, and income (X_t), and exogenous supply side or market characteristics (Z_t) that affect the costs of acquiring information. In addition, past medical care expenditures (E_{t-1}) could affect information through pathways other than health. For example, higher than expected realization of medical expenditures at the end of the year may compel individuals to gather more information about their insurance alternatives.

The Beneficiary Needs and Knowledge supplement of the Medicare Current Beneficiary Survey (MCBS) reports respondent knowledge about the insurance choice set through a series of questions which allow for 'yes', 'no' or 'don't know' responses. (These questions are listed in Section A.2 of the Appendix). I categorize the survey questions into three groups: questions related to Medicare Advantage Plans (Q^{MA}), questions related to Prescription Drug Plans (Q^{PDP}) and questions related to coverage of preventive care services through Medicare (Q^{PREV}). There is one correct answer to each of these questions. The number of correct responses provided by the beneficiary in each category measures how accurately informed she is about the insurance options/coverage benefits relevant to that category. Thus, $K_t \equiv [K_t^1, K_t^2, K_t^3]$, where K_t^1 denotes knowledge about Medicare Advantage Plans, K_t^2 denotes knowledge about Prescription Drug Plans and K_t^3 denotes knowledge about coverage of preventive care services offered through Medicare.[6] Entering period t, the individual observes the state variables $\Omega_t = [R_t, L_t, G_t, E_{t-1}, X_t, Z_t]$ where $Z_t = [Z_t^K, Z_t^{\mathcal{I}}, Z_t^F, Z_t^M, Z_t^H]$. The value of a given information level (k_1, k_2, k_3) measured by k_1 correct responses to questions relevant to Medicare Advantage plans, k_2 correct responses to questions relevant to PDPs, and k_3 correct responses to questions relevant to preventive care

[6]Knowledge about preventive care services directly affects utilization of these services, but it could also impact insurance choice through under-estimation or over-estimation of benefits offered through Medicare. For example, if individuals incorrectly think that preventive care services are not covered by Medicare (even though they actually are), they might prefer to choose some supplemental insurance for this perceived coverage gap.

coverage benefits of Medicare, can be written as[7]

$$V^K_{k_1k_2k_3t} = v^K(R_t, L_t, G_t, E_{t-1}, X_t, Z_t, K^1_t = k_1, K^2_t = k_2, K^3_t = k_3) \quad (4.1)$$

The variation in the observed arguments of $V^K_{k_1k_2k_3t}$ (captured by the function v^K) explains only a part of the variation in K observed in the data. Unobserved individual characteristics (which may not be completely idiosyncratic) influence the number of correct responses given by the individual. These unobservables can be divided into three components. The first part, μ^K, captures permanent or time-independent unobserved individual heterogeneity that affects the value of k. The second part, ν^K_t, represents time varying unobserved individual heterogeneity that affects value of k. The third part ϵ^K_t is a serially uncorrelated error term that expresses an individual's random preference for information.

Treating the number of correct answers in each category as a continuous measure of information and taking into account the three components of unobserved heterogeneity, I model information with the following estimation equations

$$\begin{aligned} k^i = \alpha^i_0 + \alpha^i_1 R_t + \alpha^i_2 L_t + \alpha^i_3 G_t + \alpha^i_4 E_{t-1} + \alpha^i_5 X_t \\ + \alpha^i_6 Z^K_t + \alpha^i_7 Z^{\mathcal{I}}_t + \alpha^i_8 Z^F_t + \alpha^i_9 Z^M_t + \alpha^i_{10} Z^H_t + \mu^{K^i} + \nu^{K^i}_t + \epsilon^{K^i}_t \end{aligned} \quad (4.2)$$

where i=1, 2, 3 and k^i is the number of correct answers in category i and μ^{K^i} and ν^{K^i} are parameters to be estimated. While individuals in the model gather information at the beginning of each period, they may have also acquired some knowledge about their chosen insurance plan last year through medical care consumption or interactions with care personnel during the course of the year. I include insurance choice in the last period as an explanatory variable in the final estimation

[7] The function defining the value of choosing an information precision (higher precision leads to greater information) is derived from a theoretical model of endogenous information choice provided in the appendix. (For details, refer to equation A.5 in Section A.1 of the Appendix.) Since the actual information depends on the precision chosen by the individual and a random component, the arguments of the value function for information are the same as the arguments for the value function of information precision.

equations for information (equation 4.2) to allow for such learning effects. The demand for different categories of information are correlated through both permanent individual unobservables (μ) and time-varying individual unobservables (ν_t).

2. *Insurance Choice*

Let $\mathcal{I}$ denote the set of insurance alternatives available to an elderly person listed in Table 3.1. The indirect utility of each plan depends on the plan's price (premium),[8] its non-pecuniary attributes (e.g., reputation of the provider, plan rating, and ease of filing claims), the cost-sharing and coverage characteristics associated with the plan, the individual's expectation of her medical care needs (captured by health) and medical care prices.[9] With imperfect information about plan features, individuals' perceived utility of a plan would depend on the extent of their knowledge. The expected indirect utility of choosing the insurance plan $I \in \mathcal{I}$ conditional on the individual's information is given by

$$V_{It}^{\mathcal{I}} = v^{\mathcal{I}}(R_t, L_t, G_t, E_{t-1}, X_t, Z_t^{\mathcal{I}}, Z_t^F, Z_t^H, Z_t^M, I_t = I|K_t) + u_{It}^{\mathcal{I}} \tag{4.3}$$

Decomposing the error term $u_{It}^{\mathcal{I}}$ into permanent, time varying and idiosyncratic error terms as discussed above, we obtain

$$u_{It}^{\mathcal{I}} = \mu_I^{\mathcal{I}} + \nu_{It}^{\mathcal{I}} + \epsilon_{It}^{\mathcal{I}} \tag{4.4}$$

Since individuals cannot select both FFS and Part C Medicare, I summarize the insurance plan chosen by the individual using three binary choice variables: the decision to take original FFS Medicare or an MA plan, the decision to take up Part D (PDP) or not, and the decision to get supplemental insurance or not. Let I_t^{MA} take the value 1 when the individual chooses a Medicare

---

[8]As multiple Medicare Advantage plans are typically available to the individual, premium for the broader category of Medicare Advantage plans could be thought of as the premium of the best available MA plan in terms of price and coverage and similarly, for Prescription Drug Plans and Supplemental Insurance Plans.

[9]Unfortunately, several aspects of health insurance such as coinsurance, deductibles are either not observed in the data (e.g. in case of MA plans) or do not vary across individuals (e.g. in case of Original Medicare), and, hence, cannot be included in the estimation.

Advantage Plan and 0 when FFS Medicare is chosen. I_t^{PDP} takes the value 1 when a Prescription Drug Plan (Part D) is chosen for drug coverage; 0 otherwise. I_t^{PDP} takes the value 1 when supplemental insurance is chosen; 0, otherwise.

Substituting equation 4.4 into 4.3 we get

$$V_{It}^{\mathcal{I}} = \upsilon^{\mathcal{I}}(R_t, L_t, G_t, E_{t-1}, X_t, Z_t^{\mathcal{I}}, Z_t^{F}, Z_t^{H}, Z_t^{M}, I_t = I|K_t) + \mu_I^{\mathcal{I}} + \nu_{It}^{\mathcal{I}} + \epsilon_{It}^{\mathcal{I}} \tag{4.5}$$

Approximating the $\upsilon^{\mathcal{I}}(.)$ function in 4.5 with a series expansion of its arguments and assuming a type I extreme value distribution for the idiosyncratic error term $\epsilon_{It}^{\mathcal{I}}$, the log odds ratio of choosing I_t^j is given by the following expression.

$$ln\left[\frac{\Pr(I_t^j = 1)}{\Pr(I_t^j = 0)}\right] = \beta_0 + \beta_1^j R_t + \beta_2^j L_t + \beta_3^j G_t + \beta_4^j X_t + \beta_5^j I_{t-1} + \beta_6^j E_{t-1} + \beta_7^j k_t^1 + \beta_8^j k_t^2 + \beta_9^j k_t^3$$
$$+ \beta_7^j Z_t^{\mathcal{I}} + \beta_8^j Z_t^F + \beta_9^j Z_t^M + \beta_{10}^j Z_t^H + \mu_j^{\mathcal{I}} + \nu_{jt}^{\mathcal{I}} + \epsilon_{jt}^{\mathcal{I}} \tag{4.6}$$

where j= MA, PDP, SUPP.

Certain subgroups of the elderly population qualify for additional coverage options such as Medicaid (dual eligibility on the basis of income) or VA coverage (eligibility due to veteran status). These coverage options cannot be ‘chosen’ by the beneficiaries at will and hence cannot be included in a single choice set for all individuals. At the same time, eligibility for these additional options is surely expected to have implications for their coverage. For example, full Medicaid status covers prescription drugs, thus making Part D plans redundant for such beneficiaries. Similarly, coverage available to veterans through VA may also include prescription drugs. Some states also mandate automatic enrollment in managed care plans for Medicaid eligible individuals. One way of dealing with this issue could be to allow the choice set to vary by the eligibility of the beneficiaries for programs such as Medicaid, VA coverage, and Employer Offered Insurance (ESI).

However, while it is possible to completely specify the choice set a dual eligible or a veteran beneficiary, the data used in this study is not rich enough to identify the actual plan choice made in such cases.[10] Thus, I keep a single choice set (as in Table 3.1) common to all beneficiaries and treat 'dual eligibility', 'veteran status' and 'access to employer sponsored insurance' as additional individual characteristics that explain the probabilities of having an MA plan, a PDP or supplemental insurance as well as the other dependent variables of the model. I also allow lagged insurance (I_{t-1}) in the estimation equation to capture inertia effects in health insurance plan choice.

3. *Demand for Preventive Care*

After the insurance plan is has been selected, the individual can choose to seek preventive care services (which include screenings such as mammogram, cardiovascular screening, flushots, and routine eye exams). Utilization of preventive care services can lead to early detection of health problems and can prevent greater deterioration of health in the future. Since I do not assume that all features of the chosen insurance plan are revealed automatically after the selection of the plan, this decision is conditional on the information possessed by the individual and the insurance plan chosen. Most preventive care services are covered under Medicare.[11] Hence, less knowledge about coverage of preventive care services generally implies that the individual either incorrectly thinks that the preventive care service is not covered or is uncertain about it, when it is actually covered, leading to under-utilization of these services.

F_t is a binary variable that takes the value 1 when a female uses one or more of the four preventive care services (mammogram, papsmear, flushot, eye exam) or when a male uses one or more of three services (PSA blood test, flushot, eyeexam). Incidence of cancer increases exponentially with advancing age and cancer screenings are the most recommended forms of preventive care for senior citizens (Berger et al., 2006).[12]

[10]For example, we cannot distinguish between individuals with full versus part Medicaid eligibility or between a Medicaid managed care plan versus a FFS plan.

[11]Exceptions are routine eye exams and dental check-ups.

[12]Data considerations also drive the selection of these particular services. Because the claims data for MA plan holders is not complete, use of survey data for utilization of preventive care services is preferred.

The value function for preventive care and its arguments are:

$$V_{ft}^F = v^F(R_t, L_t, G_t, X_t, E_{t-1}, Z_t^F, Z_t^M, Z_t^H | K_t, I_t) + u_{ft}^F \tag{4.7}$$

which leads to the following estimation equation:

$$\begin{aligned} ln\left[\frac{\Pr(F_t=1)}{\Pr(F_t=0)}\right] &= \gamma_0 + \gamma_1 R_t + \gamma_2 L_t + \gamma_3 G_t \\ &+ \gamma_4 X_t + \gamma_5 E_{t-1} + \gamma_6 k_t^1 + \gamma_7 k_t^2 + \gamma_8 k_t^3 + \gamma_9 I_t^{MA} + \gamma_{10} I_t^{PDP} + \gamma_{11} I_t^{SUPP} \\ &+ \gamma_{12} Z_t^F + \gamma_{13} Z_t^M + \gamma_{14} Z_t^H + \mu^F + \nu_t^F + \epsilon_t^F \end{aligned} \tag{4.8}$$

4. *Health Shock*

The Medicare Current Beneficiary Survey (MCBS) provides detailed survey data on the beneficiaries' chronic conditions and the complications associated with these chronic conditions. A health shock is defined as an onset of a new chronic condition related to heart problems, respiratory problems, cancer and diabetes (since these are the most common disabling conditions among the elderly and they also tend to be the cost drivers of elderly medical expenditures (Wolff et al., 2002; Yang et al., 2009). Individuals with existing chronic conditions can also experience a health shock if severity of these conditions increases.[13] An adverse health shock (S_t=1) implies that the individual's severity adjusted chronic conditions increases by 1 in the next period (i.e., $R_{t+1} = R_t + 1$).

The log odds ratio of having a health shock in period t relative to not having a health shock is given by

$$ln\left[\frac{\Pr(S_t=1)}{\Pr(S_t=0)}\right] = \delta_0 + \delta_1 R_t + \delta_2 L_t + \delta_3 G_t + \delta_4 X_t + \delta_5 F_t + \delta_6 Z_t^H + \mu^S + \nu_t^S \tag{4.9}$$

Health status entering the period (R_t, L_t, G_t), demographic characteristics (X_t), and the utilization of preventive care services (F_t) affect the probability of experiencing a health shock. County and

[13]For example, severity increases if an individual with an existing heart condition experiences increased hypertension, high cholestrol, hardening of the arteries or an individual with diabetes experiences eye problems.

year differences in health-related exogenous variables (Z_t^H) also influence the onset of a chronic condition or an increase in complications associated with a condition. These health shocks are correlated with permanent and time-varying unobservables that determine the other behaviors (information seeking, insurance and preventive care selection, medical care demand and functionality transitions) captured by μ^S and ν_t^S in the above estimation equation.

5. *Medical Care Demand and Expenditures*

The demand for medical care is derived from its effect on the individual's lifetime utility which consists of two parts: the contemporaneous utility, and the expected present discounted value of utility in the future conditional on medical care choices in the period. Medical care utilization affects contemporaneous utility through its effect on expenditures on medical care (and hence, consumption). This effect on current period utility varies with the health insurance selected for the period (I_t) and exogenous prices of medical care (Z_t^M). Expected future utility from medical care consumption this period depends on the effectiveness of medical care in maintaining or improving health next period which varies with observed health shocks (S_t), as well as health status entering the period ($H_t \equiv (R_t, L_t, G_t)$). I also allow lagged medical care expenditure to affect current medical consumption through channels other than health.[14]

The value function corresponding to a choice of medical care with its arguments is given by

$$V_{an}^M = v^M(R_t, L_t, G_t, E_{t-1}, X_t, A_t = a, N_t = n | K_t, I_t, F_t, S_t) + u_{ant}^M \tag{4.10}$$

A_t is measured by the number of inpatient events during the course of the year and N_t is the total number of outpatient and prescription drug events in the decision year. Since there is considerable skewness in the utilization of inpatient services (around 30 per cent of the individuals do not have any inpatient events and a small percentage have extremely high number of such events), I model annual (log) utilization of inpatient services as the joint product of the probability of any utilization

[14]For example, hospitalizations in the previous period could necessitate follow-ups, physician visits or drug use in future periods.

(using a logit equation) and the log of utilization, if any (treated as a continuous outcome). Since the estimation sample consists largely of the elderly, only 3 per cent of the individuals do not use any outpatient services or drugs (N_t). Hence, I simply model log of N_t for utilization of outpatient services and drugs. The probability of any inpatient utilization (A_t) is given by:

$$
\begin{aligned}
ln\left[\frac{\Pr(A_t > 0)}{\Pr(A_t = 0)}\right] &= \lambda_0 + \lambda_1 R_t + \lambda_2 L_t + \lambda_3 G_t \\
&\quad + \lambda_4 X_t + \lambda_5 E_{t-1} + \lambda_6 S_t + \lambda_7 I_t^{MA} + \lambda_8 I_t^{PDP} + \lambda_9 I_t^{SUPP} \\
&\quad + \lambda_{10} k_t^1 + \lambda_{11} k_t^2 + \lambda_{12} k_t^3 + \lambda_{13} Z_t^M + \mu^{A1} + \nu_t^{A1} \quad (4.11)
\end{aligned}
$$

Log use of inpatient service use, A_t, is modeled as:

$$
\begin{aligned}
ln(A_t | A_t > 0) &= \psi_0 + \psi_1 R_t + \psi_2 L_t + \psi_3 G_t \\
&\quad + \psi_4 X_t + \psi_5 E_{t-1} + \psi_6 S_t + \psi_7 I_t^{MA} + \psi_8 I_t^{PDP} + \psi_9 I_t^{SUPP} \\
&\quad + \psi_{10} k_t^1 + \psi_{11} k_t^2 + \psi_{12} k_t^3 + \psi_{13} Z_t^M + \mu^{A2} + \nu_t^{A2} \quad (4.12)
\end{aligned}
$$

and log use of outpatient services and prescription drug utilization, N_t, is modeled as:

$$
\begin{aligned}
ln(N_t) &= \tau_0 + \tau_1 R_t + \tau_2 L_t + \tau_3 G_t \\
&\quad + \tau_4 X_t + \tau_5 E_{t-1} + \tau_6 S_t + \tau_7 F_t + \tau_8 I_t^{MA} + \tau_9 I_t^{PDP} + \tau_{10} I_t^{SUPP} \\
&\quad + \tau_{11} k_t^1 + \tau_{12} k_t^2 + \tau_{13} k_t^3 + \tau_{14} Z_t^M + \mu^N + \nu_t^N \quad (4.13)
\end{aligned}
$$

The demands for each type of medical care are estimated jointly (along with information, insurance, shocks, and health production) and are correlated through both permanent individual unobservables (μ) and contemporaneous time-varying individual unobservables (ν_t).

Once the individual selects medical care, her medical expenditures are determined as a function of her chosen insurance plan, total utilization and medical care prices in her area of residence.

Apart from the indirect effect of information on medical expenditures through its effect on insurance choice, and, preventive and medical care utilization, the estimation equation allows for independent effects of information on expenditures. Three types of medical expenditures are modeled: total medical expenditures (incurred by the provider and the individual) corresponding to the A_t utilization, E_t^A; total medical expenditures corresponding to N_t utilization, E_t^N; and, total out-of-pocket expenditures of the individual (including insurance payments), E_t^O. Thus, the estimation equation for total medical expenditures on inpatient services is given by:

$$\begin{aligned} ln(E_t^A|A_t>0) = \tau_0^A + \tau_1^A R_t + \tau_2^A L_t + \tau_3^A G_t \\ + \tau_4^A X_t + \tau_5^A A_t + \tau_6^A S_t + \tau_7^A I_t^{MA} + \tau_8^A I_t^{PDP} + \tau_9^A I_t^{SUPP} \\ + \tau_{10}^A k_t^1 + \tau_{11}^A k_t^2 + \tau_{12}^A k_t^3 + \tau_{13}^A Z_t^M + \mu^{E^A} + \nu_t^{E^A} \end{aligned} \tag{4.14}$$

The estimation equation for total medical expenditures on outpatient services and drugs is:

$$\begin{aligned} ln(E_t^N) = \tau_0^N + \tau_1^N R_t + \tau_2^N L_t + \tau_3^N G_t \\ + \tau_4^N X_t + \tau_5^N N_t + \tau_6^N S_t + \tau_7^N I_t^{MA} + \tau_8^N I_t^{PDP} + \tau_9^N I_t^{SUPP} \\ + \tau_{10}^N k_t^1 + \tau_{11}^N k_t^2 + \tau_{12}^N k_t^3 + \tau_{13}^N Z_t^M + \mu^{E^N} + \nu_t^{E^N} \end{aligned} \tag{4.15}$$

and the equation for total out-of-pocket expenditures is:

$$\begin{aligned} ln(E_t^O) = \tau_0^O + \tau_1^O R_t + \tau_2^O L_t + \tau_3^O G_t \\ + \tau_4^O X_t + \tau_5^O A_t + \tau_6^O N_t + \tau_7^O S_t + \tau_8^O I_t^{MA} + \tau_9^O I_t^{PDP} + \tau_{10}^O I_t^{SUPP} \\ + \tau_{11}^O k_t^1 + \tau_{12}^O k_t^2 + \tau_{13}^O k_t^3 + \tau_{14}^O Z_t^M + \mu^{E^O} + \nu_t^{E^O} \end{aligned} \tag{4.16}$$

6. *Health Production*

Apart from the number of severity adjusted chronic conditions (R_t) which are automatically updated from the initial number of conditions and the value of the shock variable, I model two additional measures of health: functional status (L_t) and self-reported health (G_t). Functional status is an objective measure of health capturing the number of ADL(Activities of Daily Living) limitations and number of IADL(Instrumental Activities of Daily Living) limitations. More specifically, the functional status is a categorical variable that takes the value, $L_{t+1} = 0$, when there are no ADL or IADL limitations and $L_{t+1} = 1$, when the individual has at least one IADL limitation and up to two ADL limitations (moderate disability), $L_{t+1} = 2$, when there are more than two limitations (severe disability), and $L_{t+1} = 3$, when the individual realizes the extreme outcome of death in the next period. The log odds of functional status relative to no limitation in functions is specified as:

$$ln\left[\frac{\Pr(L_{t+1}=a)}{\Pr(L_{t+1}=0)}\right] = \chi_1^a R_t + \chi_2^a L_t + \chi_3^a G_t + \chi_4^a S_t + \chi_5^a S_t A_t + \chi_6^a S_t N_t + \chi_7^a X_t$$
$$+ \chi_8^a R_t A_t + \chi_9^a R_t N_t + \chi_{10}^a \mathbf{1}(L_t = 1) A_t + \chi_{11}^a \mathbf{1}(L_t = 1) N_t + \chi_{12}^a \mathbf{1}(L_t = 2) A_t + \chi_{13}^a \mathbf{1}(L_t = 2) N_t$$
$$+ \chi_{14}^a G_t A_t + \chi_{15}^a G_t N_t + \mu^{aL} + \nu_t^{aL} \quad (4.17)$$

where a=1, 2 or 3.

Interactions of shock with medical care use are included to capture the impact of medical care in tempering the effect of shocks on health. Interactions of the two types of medical care with the number of severity-adjusted chronic conditions, the functional status and self-reported health entering the period are also included to allow the productivity of medical care to differ by health status.

The third measure of health used in the model is self-reported health. In the survey data, individuals report their health ranging from excellent to poor. This subjective measure of health is treated as a continuous variable for the purpose of estimation.[15]

$$G_{t+1} = \chi_1^G R_t + \chi_2^G L_t + \chi_3^G G_t + \chi_4^G S_t + \chi_5^G S_t A_t + \chi_6^G S_t N_t + \chi_7^G X_t$$
$$+ \chi_8^G R_t A_t + \chi_9^G R_t N_t + \chi_{10}^G \mathbf{1}(L_t = 1) A_t + \chi_{11}^G \mathbf{1}(L_t = 1) N_t + \chi_{12}^G \mathbf{1}(L_t = 2) A_t + \chi_{13}^G \mathbf{1}(L_t = 2) N_t$$
$$+ \chi_{14}^G G_t A_t + \chi_{15}^G G_t N_t + \mu^G + \nu_t^G \quad (4.18)$$

The dynamics of health are captured by the dependence of functional status and self-reported health next period on endogenous values of current functional status and self-reported health. Additionally, health transitions are dynamic because they depend on medical care consumption in the current period. It should be noted that health production depends on other inputs such as nutrition, exercise, and risky behaviors (e.g., smoking) which are not modeled in this research due to lack of data. These omitted inputs are a part of the unobserved heterogeneity in the model. For example, proclivity to engage in risky behaviors like smoking is likely to be a permanent characteristic of the individual and hence gets included in the μ component which persists over time. Other unobservables (such as health shocks not captured by chronic conditions) are modeled as part of the time-varying component of the unobserved heterogeneity, ν_t.

Table 4.1 displays the dependent variables and the explanatory variables for the jointly estimated system of equations in the model.

7. *Initial Conditions*

Additional reduced-form equations are included in the model to explain the initially-observed values of functional status, the number of severity-adjusted chronic conditions, self-reported health, insurance plan choice and medical care expenditures. These initial conditions cannot be modeled using the dynamic equations described above because we do not observe the previous behavior that influences their outcomes. Hence, the initial conditions are reduced-form analogs of the dynamic demand and health production equations with appropriate exogenous variables included for

[15]There are five categories of self-reported health and a multinomial logit model would considerably increase the number of parameters to be estimated.

Table 4.1: Summary of Equation Specifications

Dependent Variable	Estimator	Explanatory Variables		
		Endogenous	Exogenous	Unobs'd het
K_t	OLS	H_t, E_{t-1}, I_{t-1}	$X_t, Z_t^K, Z_t^I, Z_t^F, Z_t^M, Z_t^H$	μ^K, ν_t^K
I_t	Logit	$H_t, E_{t-1}, I_{t-1}, K_t$	$X_t, Z_t^I, Z_t^F, Z_t^M, Z_t^H$	μ^I, ν_t^I
F_t	Logit	H_t, E_{t-1}, K_t, I_t	X_t, Z_t^F, Z_t^M, Z_t^H	μ^F, ν_t^F
S_t	Logit	H_t, F_t	X_t, Z_t^H	μ^S, ν_t^S
M_t	OLS	$H_t, E_{t-1}, K_t, I_t, S_t$	X_t, Z_t^M	μ^M, ν_t^M
E_t	OLS	H_t, K_t, I_t, S_t, M_t	X_t, Z_t^M	μ^E, ν_t^E
H_{t+1}	Mlogit	H_t, S_t, M_t	X_t	μ^H, ν_t^H

identification. A description of the initial condition specifications is provided in Section A.3 of the Appendix.

CHAPTER 5

ESTIMATION AND IDENTIFICATION

The demand and production functions specified above form the set of jointly estimated equations of the empirical model. These equations are correlated through observed explanatory variables, as well as permanent (μ) and time varying (ν_t) unobservables that enter each equation. This specification of the unobserved heterogeneity[1] allows for serial correlation within outcomes over time as well as two different sources of correlation across outcomes. The permanent heterogeneity is captured by the joint distribution of

$$\mu = [\mu^K, \mu^{\mathcal{I}}, \mu^F, \mu^S, \mu^{A1}, \mu^{A2}, \mu^N, \mu^E, \mu^L, \mu^G].$$

Similarly, time-varying heterogeneity is defined by the joint distribution of

$$\nu_t = [\nu_t^K, \nu_t^{\mathcal{I}}, \nu_t^F, \nu_t^S, \nu_t^{A1}, \nu_t^{A2}, \nu_t^N, \nu_t^E, \nu_t^L, \nu_t^G].$$

Instead of imposing a specific form (such as normal) on these multivariate distributions, I model the unobserved heterogeneity as random effects and approximate its unknown distribution discretely, estimating both the mass points along the support of the unobserved components as well as the associated probability weights. This flexible estimation technique, termed as Discrete Factor Random Effects(DFRE) (Heckman and Singer, 1984; Mroz and Guilkey, 1992; Mroz, 1999), has been used in a wide variety of empirical applications including health.[2] The DFRE method performs

[1]Model estimation must account for unobserved heterogeneity (which could produce a spurious correlation between dependent variables and endogenous explanatory variables), in order to reduce the bias in estimated coefficients that arises from inclusion of endogenous variables, omission of relevant variables or measurement error.

[2]See Blau and Gilleskie (2001); Mello et al. (2002); Yang et al. (2009); and Fout and Gilleskie (2015).

as well as maximum likelihood estimation assuming normality, when the true distribution of the error terms is jointly normal and performs better (in terms of precision and bias) when the true distribution is not normal. The DFRE approach allows unobservable (to the researcher) individual characteristics to impact all jointly- estimated equations and integrates over their distributions when constructing the likelihood function. Specification of the likelihood function is provided in Section A.4 of the Appendix.

Estimation of dynamic equations with panel data requires exogeneity of some explanatory variables conditional on the unobserved heterogeneity. The system of dynamic equations is, in part, identified by the inclusion of exogenous, theoretically relevant variables, Z_t =(Z_t^K, $Z_t^{\mathcal{I}}$, Z_t^F, Z^M, Z_t^H) that affect the behavior/outcome in one equation but do not affect other endogenous variables independently. A description of these identifying Z variables, the data sources and the specific equations in which they belong is provided in Table 5.1.

The 'Medicare and You' book is a comprehensive book providing a detailed description of all insurance options available through Medicare and is mailed to all current beneficiaries but may not be received by some elderly persons due to exogenous factors such as a change of address or loss of mail. Whether the individual receives the book or not, affects information but, conditional on her knowledge, does not impact subsequent choices of insurance, medical care, or the health production process. Similarly, having a personal computer at home impacts an individual's information but does not impact her other choices or outcomes independent of its effect on information. Number of MA plans and PDPs, and their average premiums, in the beneficiary's area, are supply side factors that affect the choice of insurance. But conditional on the insurance plan chosen, these factors do not affect subsequent decisions and outcomes. Similarly, the number of hospitals with full-field digital mammography techniques and the number of radiology technicians per thousand population determine the access and quality of preventive medical services available to the beneficiary but do not have independent effects on choice of medical care or the production of health. The number of hospitals, hospital beds, physician-dentists, and licensed pharmacists per thousand population capture the individual's access to curative medical care services, thus affecting utilization of these services. The median air quality index (a measure of air quality that is provided by the Environmental Protection Agency), at the county level, is used as an exogenous shifter of health. Conditional on the unobserved heterogeneity (μ and ν_t), lagged values of the endogenous variables also aid identification (assuming no serial correlation in the remaining errors). Finally, functional forms of the non-linear equations (the logit and the multinomial logits) of the model provide identification.

Table 5.1: Description of Exogenous Identifying Variables

Dependent Variable	Exclusion Restrictions	Source	level
Information	Beneficiary received Medicare and You Book?	MCBS	individual
	Beneficiary has personal computer at home?	MCBS	individual
Insurance	No. of MA plans in beneficiary area	MCBS	individual
	No. of PDP plans in beneficiary area	KFF	state
	Average PDP plan premium in beneficiary area	KFF	state
Preventive Care	No. of radiology techs per thousand	AHRF	county
	No. of hospitals with full-field digit mammography	AHRF	county
Medical care	Medicare Part A reimbursement rate	AHRF	county
	No. of hospitals per thousand	AHRF	county
	No. of hospital beds per thousand	AHRF	county
	No. of physician-dentists per thousand	AHRF	county
	No. of licensed pharmacists	AHRF	county
	No. of pharma techs per thousand	AHRF	county
Health	Median Air Quality Index	EPA	county

AHRF: Area Health Resource Files (2006-11) , KFF- Kaiser Family Foundation State health facts
EPA- Environmental Protection Agency

CHAPTER 6

DATA

The Medicare Current Beneficiary Survey (MCBS) is a longitudinal survey of Medicare beneficiaries conducted by the Centers for Medicare and Medicaid Services (CMS). The MCBS files combine survey data from the beneficiaries with claims data to provide a complete picture of medical care utilization and expenditures. As part of the survey data, respondents answer questions about demographics, health insurance, health status and medical events and expenditures. Respondents are followed for a maximum period of four years after which they are phased out to introduce new participants, keeping the overall cross-sectional demographic composition of the survey constant across years.

This study uses MCBS files from 2006 to 2011. As Medicare Part D went into effect in 2006, the number of choices available increased considerably.[1] Due to the rotating panel nature of the data, respondents are observed for varying numbers of years from 2006-2011.[2] There is relatively little attrition due to non-response.

For the construction of the final estimation sample, younger individuals who qualify for Medicare due to disability status or End Stage Renal Disease (ESRD) are dropped from the analysis as these individuals are likely to be much different from the elderly population with Medicare. Individuals living in long-term care facilities are also excluded from the analysis.[3] I also excluded beneficiaries whose survey information was completed by their proxies and individuals who reported not selecting their own insurance plan (i.e., their plan was chosen by a proxy, usually an

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[1] 2011 is the last year of complete data available from CMS.

[2] For example, beneficiaries who entered the survey in 2004 are observed for only two years (2006 and 2007) in the estimation sample.

[3] It is unlikely that these individuals would be making their own health insurance and medical care decisions.

adult child or a spouse). However, respondents who report receiving help on their insurance decisions are included in the sample.[4] Table 6.1 provides additional information on the sample used for estimation, which consists of 17,813 individuals who contribute 52,282 person-year observations.

Table 6.1: Empirical Distribution of Sample Participants

Years followed	Number of individuals	Percentage of Sample
At least 2 years	17,813	100
At least 3 years	10,923	61.32
At least 4 years	5,733	32.18
Exactly 2 years	6,890	38.68
Exactly 3 years	5,190	29.14
Exactly 4 years	5,733	32.18
2006	7,531	14.40
2007	10,245	19.60
2008	9,417	18.01
2009	9,197	17.59
2010	9,282	17.75
2011	6,610	12.64
Number of unique individuals	17,813	
Number of person-year observations	52,282	

Information possessed by an individual regarding Medicare Advantage plans is measured by the number of correct responses to Medicare Advantage related questions[5] and similarly for Prescription Drug plans and preventive care coverage benefits of Medicare. Only 22 per cent of the elderly give all correct responses to Medicare Advantage related questions and approximately the same percentage give all incorrect answers. The percentage of elderly who give all correct responses to Prescription Drug Coverage (PDP) related questions is 32 per cent while less than 13 per cent answer all drug coverage related questions incorrectly.

Table 6.2 shows one-year transitions in the number of correct MA responses given by the sample participants. While we observe some persistence in information, it is clear that there is

[4]Whether the individual received help in insurance selection or not is controlled for in the estimation equations.

[5]See Section A.2 of the Appendix for the list of questions used in construction of information measures.

considerable movement across information categories too (i.e., individuals acquire and lose (forget) information). The average information possessed generally declines with age suggesting the importance of cognitive costs in acquiring information (Figure 6.1).[6]

FFS Medicare is the primary form of health insurance (69 per cent) chosen by the elderly. Just over half(54 per cent) of the beneficiaries choose a Prescription Drug Plan for drug coverage and 66 per cent have some form of supplemental insurance (e.g., Medigap, Employer Sponsored Insurance (ESI)).

Table 6.2: One Year Information Transitions

# correct MA responses(t-1)	# correct MA responses(t)				
	0	1	2	3	Total
0	38	27	21	14	100
1	23	31	27	19	100
2	15	22	33	29	100
3	9	16	30	45	100
Total	21	24	28	26	100

Source: MCBS. The numbers show the percentage of sample participants in each information category.

The average annual expenditures on inpatient services (covered by Part A) and outpatient services and prescription drugs (combined) during this time period were \$7,838 and \$8,341 respectively. While Part A expenditures increase with age, expenditures on outpatient events and drugs follow a U-shaped pattern (Figure 6.3). The average individual out-of-pocket expenditures (including insurance premiums) of sample participants was \$2,211, which also shows an increasing trend with age.

Health status is measured by two objective measures: functional status and the number of chronic conditions. Functional status is measured by the number of Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs) reported in the survey files of the

[6]Solid lines represent the observed statistics from the actual sample. The simulated observations indicated by dashed lines are discussed later in Chapter 7.

Figure 6.1: Actual and Simulated Number of Correct Responses, by Age

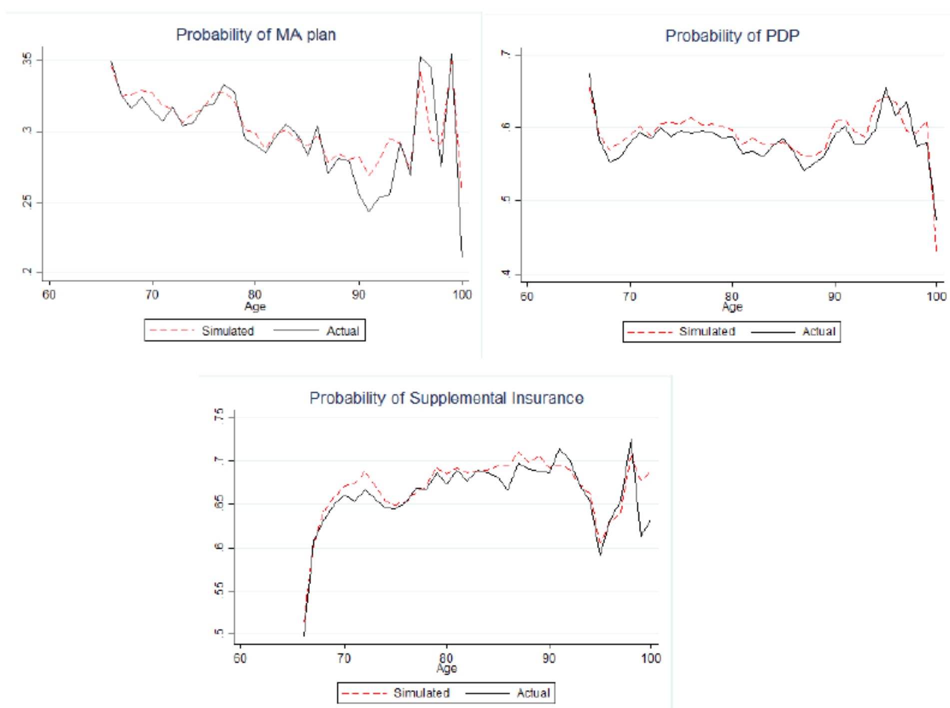

Figure 6.2: Actual and Simulated Probability of Different Types of Insurance, by Age

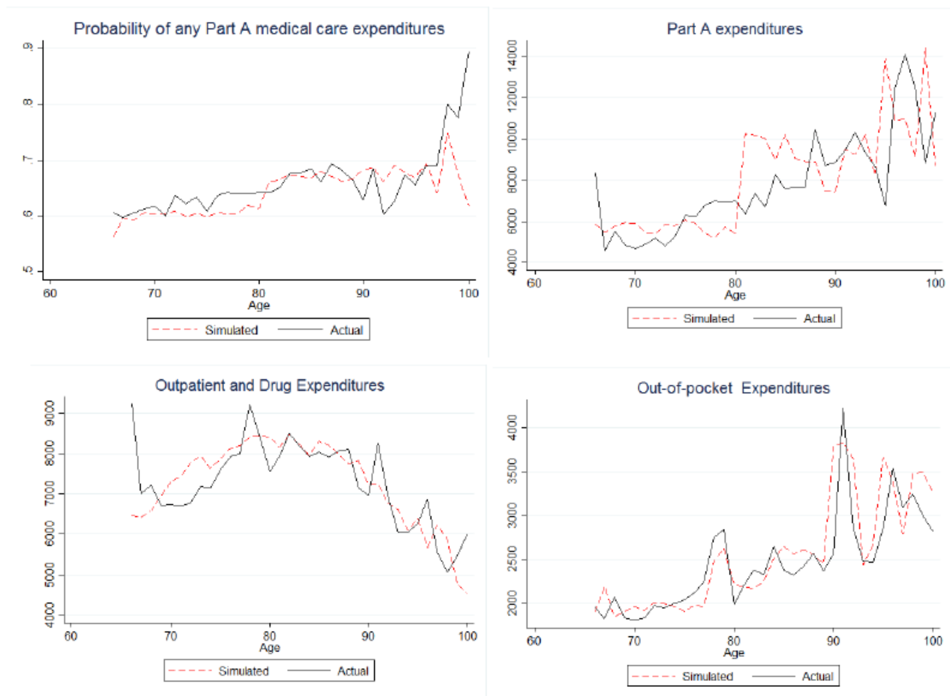

Figure 6.3: Actual and Simulated Medical Care Expenditures, by Age

MCBS. Approximately 14 per cent of the sample respondents report having moderate disability with at least one IADL and with no more than two ADLs and 8 per cent report having severe disability with three or more ADLs. The MCBS survey data provides detailed information on the beneficiaries' chronic conditions and severity of these conditions. Four different types of chronic conditions — heart, respiratory, cancer and diabetes — are considered for constructing the initial number of chronic conditions. This number (measuring severity-adjusted chronic conditions) is updated with the development of a new condition or an increase in severity of an existing one. Self-reported health on a scale of 1 (poor) to 5 (excellent) is used as a measure of an individual's subjective evaluation of her health.

Table 6.3 describes the individual-specific demographic variables used to explain information, insurance selection, medical care use and expenditures and health status. The dependent variables — information, insurance, preventive and medical care use, medical expenditures and health — are used as endogenous explanatory variables in the relevant equations determined by the timing

Table 6.3: Description of Exogenous Individual Variables

Variable Name	Mean	Standard Deviation
Time-invariant individual characteristics		
Years of schooling (range:10-19 years)	13.76	3.19
Female (omitted: male)	0.58	0.49
Race (omitted: white)		
Black	0.08	0.27
Other Race	0.05	0.21
Time-varying individual characteristics		
Age (range: 65-105)	76.80	7.24
Rural (omitted: Urban)	0.26	0.44
Not married (omitted: Married)	0.47	0.50
Annual Income (000's of year 2011 dollars)	29.32	51.42

of the model. Additionally, exogenous variables (usually capturing supply and price conditions) specified in Table 5.1 are used as explanatory variables.

Figure 6.4 shows the unconditional relationship between insurance choice and out-of-pocket expenditures. Relative to FFS Medicare, out-of-pocket expenditures associated with a Medicare Advantage Plan are lower across the age distribution. Average individual out-of-pocket expenditures are somewhat lower for those without a Prescription Drug Plan, particularly, in the early ages. However, the variation in out-of-pocket expenditures is higher for individuals without a Prescription Drug Plan. For consumers who choose to buy supplemental insurance, average out-of-pocket expenditures are higher at all ages relative to those who do not have supplemental insurance. As we would expect, the variance associated with out-of-pocket expenditures across the age distribution is lower with the purchase of supplemental insurance. Figure 6.5 shows the unconditional relationship between information and insurance choices in the data. For the purpose of this graph, an individual is 'more informed' if they are able to answer at least two Medicare Advantage related questions, at least two Prescription Drug Plan related questions and at least five questions related to Medicare coverage of preventive care.[7] An individual is 'less informed' if the number of correct

[7] Approximately, 20 per cent of the sample are 'more informed' and 16 percent are 'less informed'.

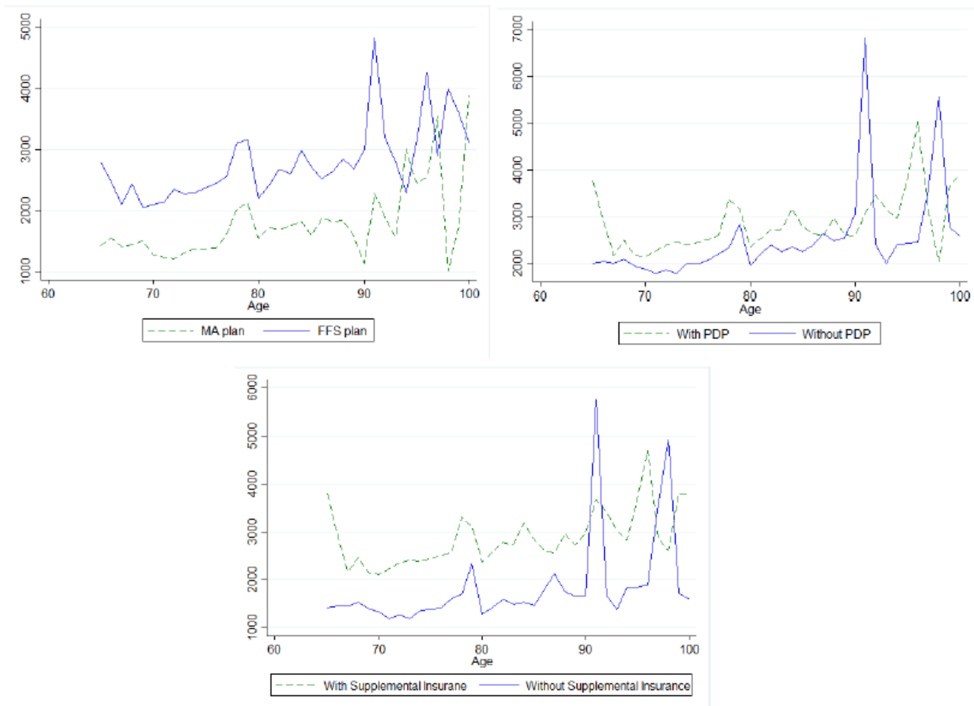

Figure 6.4: Out-of-Pocket Expenditures, by Insurance Choice

answers to Medicare Advantage and PDP related questions is less than one each and the number of correct answers to preventive care related questions is less than 3. As seen in the graph, the probability of selecting a Medicare Advantage plan is much higher in the group that is more informed at all ages. The same relationship is found with the choice of a Prescription Drug Plan. However, the probability of selecting supplemental insurance does not differ across the more and less informed subgroups of individuals.

While it is informative to look at the unconditional relationships between the outcomes of interest in the data, the dynamic causal relationships between them can be established only through estimation of the empirical model (specified in Chapter 5), which takes into account the sequential nature of the decision making and controls for the unobserved heterogeneity. To this end, we proceed to Chapter 7 to discuss the results obtained from model estimation.

Figure 6.5: Choice of Insurance Plan, by Information

CHAPTER 7

RESULTS

In the first part of this chapter, I discuss the signs and significance of the coefficients of the main explanatory variables in the estimation equations. These numbers describe the qualitative, short-term (static) effects. Three mass points (each) were found to be sufficient for capturing the distributions of permanent and time varying individual unobserved heterogeneity that is likely to influence choices and outcomes of the model.[1] In the second part of this chapter, I discuss the model fit and results from five-year simulations of the jointly estimated system of equations under alternate information scenarios that impact endogenous state variables over time. These results illustrate the long-term, dynamic effects of information.

7.1 Parameter Estimates

I begin by examining the factors that explain the heterogeneity in information observed in the data, followed by an analysis of the impact of imperfect information on individual choices and outcomes.

1. Information

Table 7.1 displays parameter estimates for selected variables explaining information variation in the data for each of the information categories. The number of chronic conditions at the beginning of the period has a positive significant impact on information about MA Plans, PDPs and preventive care coverage benefits available through Medicare. Individuals with functional limitations (moderately disabled, severely diabled) are more likely to know about MA Plans and PDPs but have less knowledge about preventive care service coverage relative to individuals with no functional limitations. Having an MA plan or a PDP in the last period is a strong predictor (in

[1] Adding additional points of support for each discrete distribution did not improve the fit of the model.

terms of both magnitude and significance) of greater knowledge about these insurance plans. The importance of lagged insurance choices suggests that there could be 'learning through use' effects, (i.e., beneficiaries learn about their chosen plan through utilization of medical care services as they progress through the year), which combined with persistence in information[2] could explain the results.

Years of schooling and income have expected positive effects on information. Minorities (black and other non-white populations) tend to have less information than whites, all else equal. While declining age could lead to loss in cognitive abilities making information more costly to acquire, there could also be learning effects over time as beneficiaries navigate through the Medicare system each year. The negative impact of age on information suggests that cognitive costs (not captured through health status- functional limitations, number of chronic conditions or self-reported health) are important. The exogenous identifying variables — having a personal computer at home and receiving the Medicare and You Book — have a significant, positive impact on individuals' information levels.

2. Effect of information on insurance choice

The large magnitudes and significance of coefficients corresponding to the insurance plan chosen last year in Table 7.2 provide evidence for the considerable amount of persistence that exists in insurance selection. However, even after controlling for past choices, information (i.e., the number of correct responses) has a significant effect on the choice of insurance plan. In particular, individuals with greater information about MA plans and PDPs are more likely to choose these plans.[3] Beneficiaries who are more knowledgeable about the preventive care service coverage benefits of Medicare are more likely to choose a combination of Original Medicare with PDP and some form

[2]The correct answers to the questions asked in the Beneficiary Needs and Knowledge Supplement do not change considerably over the years, so information persistence is to be expected.

[3]We might expect that individuals could gain information about a product by 'experiencing' the product, thus motivating the purchase of insurance alternatives which were either not chosen in the past or are not well understood by the beneficiary (less information). However, the signs of the coefficients on lagged insurance and the information variables do not seem to support this hypothesis.

of supplemental insurance over an MA plan. Higher medical expenditures in the past have a positive impact on the probability of choosing supplemental insurance and individuals with chronic conditions are likely to choose Prescription Drug Plans for drug coverage. Parameter estimates also indicate advantageous selection in MA plans (i.e., individuals in better health who realize lower medical expenditures are more likely to select Medicare Advantage Plans).

Medicaid eligibility has a positive significant impact on the probability of having an MA plan. This may be due to mandated automatic enrollment in managed care plans in many states. The probability of enrolling in a PDP is lower with Medicaid eligibility as the full Medicaid status covers prescription drugs. Medicaid eligibility also reduces the probability of supplemental insurance, in part, due to the comprehensive benefits associated with the combination of Medicare and Medicaid. Another reason could be the eligibility criteria based on low income, which reduces the chances of supplemental insurance purchase. The VA health care system also has provisions for prescription drug coverage. As a result, beneficiaries who are eligible for VA health benefits are less likely to be enrolled in PDPs and Medicare Advantage Plans. Access to employer sponsored insurance increases the probability of enrollment in a Medicare Advantage Plan and a supplemental insurance plan.

3. Effect of information on use of preventive care services

The first column of Table 7.3 shows parameter estimates of selected variables that explain the decision to consume preventive care. While knowledge about Medicare Advantage Plans or Prescription Drug Plans does not have a significant effect on the use of preventive medical services, knowledge about coverage of these services has a significant, positive impact on the probability of utilizing preventive care. Individuals with only Original Medicare (no PDP or supplemental insurance) are considerably less likely to consume preventive care services. This finding is consistent with the fact that Original Medicare is the default option for all beneficiaries, and does not require any information acquisition. Beneficiaries are more likely to utilize preventive care as they age. The number of chronic conditions has a positive impact on the probability of using preventive care but usage declines with increase in functional limitations.

Table 7.1: Parameter Estimates for Selected Variables Explaining Information

Selected Variables	# correct MA	# correct PDP	# correct PREV
Medical Expenditure last period (/1000)	-0.007 (0.045)	-0.002 (0.003)	0.003 (0.005)
No. of chronic conditions entering the period	0.024^{***} (0.005)	0.031^{***} (0.005)	0.089^{***} (0.007)
Moderately disabled	-0.025^{*} (0.012)	-0.008 (0.017)	-0.116^{***} (0.028)
Severely disabled	0.026 (0.023)	0.058^{***} (0.023)	-0.113^{***} (0.037)
Indicator for MA plan last period	0.473^{***} (0.016)	-0.017 (0.016)	-0.071^{***} (0.026)
Indicator for PDP last period	0.095^{***} (0.012)	0.335^{***} (0.012)	0.099^{***} (0.019)
Indicator for SUPP insurance last period	-0.010 (0.016)	0.020 (0.016)	0.294^{***} (0.025)
Age	-0.014^{***} (0.003)	-0.015^{***} (0.004)	0.023^{***} (0.005)
Years of education	0.024^{***} (0.001)	0.022^{***} (0.002)	0.025^{***} (0.001)
Income (/1000)	0.003^{***} (0.001)	0.000 (0.001)	0.004^{***} (0.003)
Indicator for race black	-0.151^{***} (0.021)	-0.156^{***} (0.020)	-0.2696^{***} (0.033)
Indicator for race other	-0.159^{***} (0.028)	-0.199^{***} (0.027)	-0.22^{***} (0.043)
Have personal computer at home	0.225^{***} (0.037)	0.290^{***} (0.037)	0.572^{***} (0.059)
Received Medicare and You Book	0.111^{***} (0.032)	0.140^{***} (0.036)	0.363^{***} (0.051)

* indicates significance at the 10% level, ** indicates significance at 5% and *** indicates significance at 1%. Other explanatory variables include rest of the exogenous variables in Table 6.3, the identifying variables in Table 5.1, and, parameters for unobserved heterogeneity. I also include higher order moments and interaction terms of exogenous variables.

Table 7.2: Parameter Estimates for Selected Variables Explaining Insurance Selection

Selected Variables	MA Plan	Part D Plan	Supp. Plan
# correct MA responses	0.256^{***}	0.092^{***}	-0.151^{***}
	(0.027)	(0.025)	(0.024)
# correct PDP responses	0.032	0.252^{***}	0.048^{**}
	(0.027)	(0.025)	(0.025)
# correct Preventive care responses	-0.061^{***}	0.050^{***}	0.102^{***}
	(0.016)	(0.016)	(0.015)
Medical Expenditure last period (/1000)	-0.033^{**}	-0.004	0.029^{**}
	(0.014)	(0.013)	(0.012)
No. of chronic conditions entering the period	-0.004	0.030^{***}	-0.055^{***}
	(0.023)	(0.021)	(0.020)
Moderately disabled	0.088	0.043	-0.078
	(0.083)	(0.078)	(0.073)
Severely disabled	0.016	0.072	0.080
	(0.111)	(0.113)	(0.098)
Indicator for MA plan last period	5.328^{***}	0.504^{***}	0.175^{***}
	(0.067)	(0.072)	(0.063)
Indicator for PDP last period	0.368^{***}	5.139^{***}	-1.050^{***}
	(0.061)	(0.058)	(0.054)
Indicator for SUPP insurance last period	-0.668^{***}	-1.388^{***}	4.670^{***}
	(0.074)	(0.077)	(0.065)
Age	-0.048^{***}	-0.010	0.047^{***}
	(0.014)	(0.013)	(0.012)
Years of education	-0.012	-0.010	0.043^{***}
	(0.010)	(0.012)	(0.002)
Income (/1000)	-0.006^{***}	-0.003	0.005^{**}
	(0.002)	(0.002)	(0.002)
Indicator for race black	0.133^{***}	-0.240^{***}	-0.087^{***}
	(0.093)	(0.098)	(0.083)
Indicator for race other	-0.110^{*}	0.297^{**}	-0.233^{**}
	(0.0124)	(0.154)	(0.120)
Eligibility for Medicaid	0.568^{***}	-1.610^{***}	-0.536^{***}
	(0.091)	(0.130)	(0.079)
Eligibility for VA coverage	-0.283^{***}	-0.759^{***}	0.317^{***}
	(0.081)	(0.080)	(0.070)
Eligibility for ESI	0.111^{***}	-0.440	1.14^{***}
	(0.080)	(0.253)	(0.067)

* indicates significance at the 10% level, ** indicates significance at 5% and *** indicates significance at 1%. Other explanatory variables include the exogenous variables in Table 6.3, the identifying variables in Table 5.1, and parameters for unobserved heterogeneity. I also include higher order moments and interaction terms of exogenous variables. Full regression equations also control for Medicaid, VA and ESI eligibility along with a variable for whether the indvidual receives help on insurance decisions.

Table 7.3: Parameter Estimates for Selected Variables Explaining Preventive and Medical Care Use

Selected Variables	Preventive care	Any inpatient use	Inpatient events (log) | If any	Outpatient and Drug events (log)
Medical Expenditure last period (/1000)	0.033 (0.015)**	0.062 (0.008)***	0.018 (0.003)***	0.027 (0.002)***
No. of chronic conditions entering the period	0.118 (0.021)***	−0.050 (0.011)***	0.003 (0.005)	0.063 (0.003)***
Moderately disabled	−0.061 (0.077)	−0.042 (0.040)	0.059 (0.020)***	0.040 (0.012)***
Severely disabled	−0.601 (0.087)***	−0.458 (0.057)***	0.358 (0.025)***	0.048 (0.014)***
# correct MA responses	0.004 (0.024)	0.038 (0.013)	0.011 (0.006)	−0.009 (0.004)***
# correct PDP responses	−0.007 (0.024)	0.000 (0.013)	0.013 (0.006)*	0.016 (0.004)***
# correct Preventive care responses	0.133 (0.014)***	−0.028 (0.008)	0.003 (0.004)	0.013 (0.002)***
Indicator for MA plan	0.329 (0.063)***	0.018 (0.035)***	0.013 (0.017)	−0.204 (0.011)***
Indicator for PDP	0.289 (0.057)***	−0.004 (0.030)**	−0.022 (0.014)**	0.224 (0.010)***
Indicator for SUPP insurance	0.522 (0.060)	0.314 (0.034)***	0.077 (0.017)***	0.030 (0.011)***
Preventive care		−0.040 (0.051)	0.018 (0.030)	0.270 (0.016)***
Health shock		0.341 (0.036)***	−0.015 (0.016)	0.188 (0.009)***
Age	0.054 (0.012)***	0.020 (0.007)***	−0.006 (0.003)**	0.017 (0.002)***
Years of education	0.067 (0.010)***	0.095 (0.006)***	0.012 (0.002)***	−0.006 (0.002)***
Income (/1000)	0.014 (0.002)***	0.020 (0.001)***	−0.002 (0.000)***	−0.001 (0.000)***
Indicator for race black	−0.271 (0.074)***	−0.430 (0.046)***	0.002 (0.026)	0.045 (0.016)***
Indicator for race other	0.036 (0.102)	−0.062 (0.063)	−0.053 (0.032)**	0.080 (0.020)

* indicates significance at the 10% level, ** indicates significance at 5% and *** indicates significance at 1%. Other explanatory variables include the exogenous variables in Table 6.3, the identifying variables in Table 5.1, and parameters for unobserved heterogeneity. I also include higher order moments and interaction terms of exogenous variables Full regression equations also control for Medicaid, VA and ESI eligibility along with a variable for whether the individual receives help on insurance decisions

4. Medical care services utilization and expenditures

The last three columns of Table 7.3 show parameter estimates of selected variables that explain the different types medical care utilization. As discussed earlier, I include knowledge variables in the estimation to allow information to have independent effects on medical care utilization apart from its indirect effect through insurance and preventive care choice. Significance and magnitude of the coefficient of last year's medical expenditure, even after controlling for health status, indicates that there are certain persistence effects in medical care consumption. As expected, individuals in lower health status (moderately or severely disabled, having chronic conditions) and those who experience a health shock consume more medical care. The signs of the coefficients suggest that information, in general, has a positive impact on medical care utilization. However, the effects on inpatient utilization are smaller and usually insignificant.[4] This finding is consistent with the largely, non-discretionary nature of inpatient services. While having supplemental insurance increases utilization of all types of medical care, having a prescription drug plan is associated with lower inpatient care utilization.

Medical expenditures (both total and out-of-pocket) are a function of medical care utilization, prices (captured by the identifying Z variables in Table 5.1) and the insurance plan selected by the individual. However, insurance plans are identified only up to a broad category in the data. For example, while the researcher can observe if the beneficiary chose a PDP, she has no information regarding whether the chosen PDP was the best/most efficient/lowest cost PDP in the set of Prescription Drug Plans available to the beneficiary. This unobservable component of insurance choice can be captured, in part, by the inclusion of information variables directly in the expenditure equations (More informed individuals are more likely to have chosen the best PDP.) While information about insurance choices has either an insignificant or a positive effect on total expenditures, it has

[4]Note that consumption of preventive care services is included in outpatient and drug events. It is included as an explanatory variable in utilization of inpatient services to allow for any independent effects of preventive care use(aside from its effect through early detection of shocks).

a significant negative impact on individuals' out of pocket expenditures. Beneficiaries with Medicare Advantage plans realize lower total expenditures as well as lower out-of-pocket expenditures where as holders of supplementary insurance policies experience higher expenditures.

Since the sample used in the estimation includes dual eligible individuals, the positive effect of greater information in reducing out-of pocket expenditures may be suspect if Medicaid eligible beneficiaries are also likely to be more informed. This is because dual eligibles may realize lower out-of-pocket expenditures by simply having a more comprehensive coverage which they qualified for (instead of actually choosing it). However, coefficients of the Medicaid eligibility dummy variable in the equations for information are not significant indicates that the results, particularly with respect to the relationship between information and out-of-pocket expenditures, are not driven primarily by the inclusion of a special population like dual eligibles.

6.Functional Status Transitions

Table 7.5 displays the parameters of the estimated Grossman-style health production. Realization of a health shock reduces the probability of having no functional limitations (the omitted category). I also include interactions of health shocks with medical care consumption to examine the efficacy of medical care inputs in tempering the effect of a health shock.[5] However, these coefficients are largely insignificant and small in magnitude. Although the Medicare Current Beneficiary Survey provides relatively detailed information on health conditions, it is difficult to form an objective measure of the severity of a health shock from survey data alone. Medical care utilization reflects, in part, this unobserved (to the researcher) severity of the health shock. Hence, it is difficult to identify the productivity of medical care in combating health shocks. However, interaction terms of functional limitations at the beginning of the period with medical care utilization, clearly show, that utilization of medical inputs increases the probability of transitioning into the state with no functional limitations.

[5]Note that the information variables are not included as explanatory variables in the estimation of the health transition equations because the information considered in this research strictly pertains to individual's knowledge regarding their health insurance choice environment, and as such, it affects health transitions only through its indirect impact on medical care utilization via its effect on insurance choice.

Table 7.4: Parameter Estimates for Selected Variables Explaining Medical Care Expenditures

Selected Variables	Inpatient Service expenditures (log)	Outpatient & Drug expenditures (log)	Out-of-pocket expenditures (log)
Inpatient medical care use (/100)	0.005***		0.001**
	(0.001)		(0.000)
Outpatient and drug utilization(/100)		0.078***	0.042***
		(0.000)	(0.002)
No. of chronic conditions entering the period	0.024**	0.029***	0.010**
	(0.013)	(0.003)	(0.005)
Moderately disabled	−0.370***	−0.016*	−0.004
	(0.048)	(0.012)	(0.019)
Severely disabled	−0.756***	−0.032**	0.043**
	(0.061)	(0.016)	(0.025)
# correct MA responses	0.007	−0.001	−0.150***
	(0.016)	(0.004)	(0.006)
# correct PDP responses	−0.004	0.006*	−0.270***
	(0.016)	(0.004)	(0.006)
# correct Preventive care responses	0.014	0.009***	0.009*
	(0.010)	(0.003)	(0.004)
Indicator for MA plan	−0.064*	−0.207***	−0.076***
	(0.050)	(0.012)	(0.017)
Indicator for PDP	−0.079**	−0.084***	0.198***
	(0.035)	(0.010)	(0.015)
Indicator for SUPP insurance	0.258***	0.168***	0.493***
	(0.044)	(0.012)	(0.017)
Health Shock	0.449	0.108***	0.056***
	(0.040)	(0.010)	(0.016)
Age	−0.002	0.014***	0.008***
	(0.008)	(0.002)	(0.003)
Years of education	0.019***	0.005***	0.047***
	(0.006)	(0.002)	(0.002)
Income(/1000)	0.004**	0.002***	0.010
	(0.001)	(0.000)	(0.000)
Indicator for race black	−0.061	−0.056***	−0.374***
	(0.067)	(0.016)	(0.024)
Indicator for race other	−0.227**	0.002	−0.492***
	(0.103)	(0.021)	(0.031)

* indicates significance at the 10% level, ** indicates significance at 5% and *** indicates significance at 1%. Other explanatory variables include the exogenous variables in Table 6.3, the identifying variables in Table 5.1, and parameters for unobserved heterogeneity. I also include higher order moments and interaction terms of exogenous variables.

Table 7.5: Parameter Estimates for Selected Variables Explaining Transitions in Functional Status

Selected Variables	Moderately disabled	Severely Disabled	Mortality
No. of chronic conditions entering the period	$0.015\ (0.024)$	$-0.030\ (0.035)$	$0.134\ (0.138)$
Moderately disabled	$2.440\ (0.073)^{***}$	$3.830\ (0.111)^{***}$	$1.720\ (0.504)^{***}$
Severely disabled	$2.702\ (0.135)^{***}$	$4.970\ (0.140)^{***}$	$3.642\ (0.515)^{***}$
Health Shock	$0.230\ (0.180)^{**}$	$0.51\ (0.240)^{***}$	$0.469\ (0.730)$
Health Shock × inpatient use	$0.001\ (0.002)$	$0.001\ (0.000)^{**}$	$0.002\ (0.000)^{**}$
Health Shock × outpatient and drug use	$0.000\ (0.000)$	$0.001\ (0.002)$	$0.003\ (0.001)$
Health Shock × No. of chronic conditions	$-0.008\ (0.005)$	$-0.095\ (0.003)^{**}$	$0.006\ (0.050)$
Health Shock × Moderately Disabled	$-0.221\ {}^{(}0.031)^{***}$	$-0.331\ (0.072)^{**}$	$0.412\ (0.327)$
Health Shock × Severely Disabled	$-0.380\ (0.012)^{**}$	$-0.688\ (0.034)^{***}$	$-0.050\ (0.020)$
No. of chronic conditions × inpatient use	$0.003\ (0.000)^{***}$	$0.001\ (0.000)$	$0.000\ (0.003)$
No. of chronic conditions × outpatient & drug use	$0.007\ (0.000)^{***}$	$0.001\ (0.000)^{***}$	$0.001\ (0.015)$
Moderately Disabled × inpatient use	$-0.002\ (0.001)^{***}$	$-0.008\ (0.000)^{***}$	$-0.002\ (0.000)^{**}$
Moderately Disabled × outpatient & drug use	$-0.003\ (0.001)^{***}$	$-0.003\ (0.000)^{***}$	$-0.005\ (0.002)^{*}$
Severely Disabled × inpatient use	$-0.002\ (0.001)^{***}$	$-0.007\ (0.001)^{***}$	$-0.001\ (0.000)^{*}$
Severely Disabled × outpatient & drug use	$-0.004\ (0.002)^{***}$	$-0.004\ (0.001)^{***}$	$-0.007\ (0.004)^{**}$
Age	$0.015\ (0.010)$	$-0.009\ (0.050)$	$-0.019\ (0.038)$
Years of education	$0.000\ (0.008)$	$-0.011\ (0.021)$	$-0.007\ (0.081)$
Income(/1000)	$-0.009\ (0.002)^{***}$	$-0.008\ (0.000)^{***}$	$-0.006\ (0.004)$
Indicator for race black	$-0.202\ (0.067)^{***}$	$0.308\ (0.067)^{***}$	$0.278\ (0.314)$
Indicator for race other	$-0.095\ (0.100)$	$0.249\ (0.131)^{**}$	$-0.263\ (0.152)$

* indicates significance at the 10% level, ** indicates significance at 5% and *** indicates significance at 1%. Other explanatory variables include the exogenous variables in Table 6.3, the identifying variables in Table 5.1, and parameters for unobserved heterogeneity. I also include higher order moments and interaction terms of exogenous variables.

7.2 Simulation Results

7.2.1 Simulation Details and Model Fit

The effect of information on insurance choice, medical care demand and health outcomes in this dynamic model is best shown using simulation. The simulations quantify the long-run effect of information by incorporating the dynamic effects of behavior in the current period on future choices and health transitions.

The simulation procedure is straightforward. Given the initially observed characteristics of the individual, I use the parameters of the estimated model to simulate the number of correct answers for each information category, insurance choice, preventive care choice, health shocks and demand for medical care for the entire sample of 17,813 individuals. The simulated health shocks and medical care inputs together determine end-of-period health status and medical expenditures (endogenous state variables), which are transferred to the next period and the subsequent behavior and outcomes are again simulated using the updated state variables. This process is repeated for five years.[6] I replicate each individual multiple times allowing one draw from the permanent unobserved heterogeneity distribution and draws every year from the time-varying distribution.[7] The fit of the preferred model is demonstrated by comparing observed outcomes of the sample with model predictions using estimated model parameters and observed exogenous explanatory variables. Figure 6.1 in Chapter 6 shows how well the model (indicated by dashed line) fits the observed number of correct responses in each information category (indicated by solid line) by age. Figures 6.2 and 6.3 depict a comparison of observed and predicted probabilities of choosing different insurance plans and medical expenditures. The model fits these outcomes reasonably well, keeping in mind that the sample size gets relatively small at ages above 90.

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[6] Simulated values are used for all endogenous dependent variables but the original values (from the data) are retained for exogenous variables such as age, education, income etc. and for the identifying, Z variables.

[7] The objective is to simulate the impacts for a population whose exogenous characteristics are the same as the sample used in the study and the distribution of unobserved heterogeneity is the estimated ex-ante distribution.

7.2.2 Dynamic Effects of Greater Information

The policy question that I want to answer using simulations is: What happens to insurance choices, medical expenditures and health outcomes over time if costs of acquiring/processing information are reduced? I compare two extreme scenarios — when information costs are so low that all individuals in the model have ‘full information’ (i.e., they answer all questions correctly) and the case when information costs are prohibitive such that individuals have ‘no information’ (i.e., they answer all the questions incorrectly). The simulation procedure is the same as described above with one important exception. Information is not simulated and kept fixed (at ‘all answers correct’ or ‘no answers correct’) for all time periods as part of each policy simulation. Results from the simulations are summarized in Tables 7.6 and 7.7. The percentage of individuals choosing Medicare Advantage Plans increases by 12.72 per cent when moved from a scenario of ‘no information’ to ‘full information’. Similarly, a greater percentage of individuals supplement their Original Medicare with a Prescription Drug Plan or some form of supplemental insurance as they get more informed. The utilization of preventive care services increases by 6.17 per cent. Total expenditures on both inpatient utilization and outpatient and drug utilization increases with greater information. This effect comes from greater utilization of medical care services as individuals become more informed. However, out-of-pocket expenditures incurred by beneficiaries fall by 8.50 per cent in spite of the greater utilization of medical services. These monetary gains seem to be driven by more efficient insurance plan choices. The overall health of the sample does not show any significant changes. The proportion of individuals with moderate and severe disability over the five-year period remains the same under alternative information scenarios. A closer examination, however, reveals that the outcomes of the individuals with lower initial health status (either moderately or severely disabled) improve considerably under full information. Of the 22 per cent individuals who have some functional limitation at their first period of observation, 51.73 per cent are able to transition to the no limitation state under full information. The corresponding number for 'no information' is 40.75 per cent.[8] This positive impact of information on the 'less healthy' individuals is driven by its positive impact on medical care utilization which is an effective input in the health production process of these individuals (Table 7.5). The greater impact on health outcomes for the 'less healthy' individuals suggests that policy makers with limited resources of increasing insurance literacy should target this subgroup of the elderly.

I also examine the dynamic marginal effects of information (i.e, increasing the number of correct answers by one standard deviation from their simulated value). Results are qualitatively similar to the full vs. no information simulations and are provided in Tables 7.8 and 7.9.

Table 7.6: Five Year Simulations of Insurance and Preventive Care Choices under Full and No Information

	Full Information	No Information	Percentage Change	
Insurance Choice				
Medicare Advantage	40.34	27.62	12.72	(2.38)
Prescription Drug Plan	66.17	50.29	15.88	(3.29)
Supplemental Insurance	65.84	63.46	2.38	(2.12)
Preventive Care Choice				
Preventive Care	87.43	81.26	6.17	(1.80)

Bootstrapped standard errors are provided in parantheses. Full Information: All individuals answer all the questions correctly. No Information: All individuals answer all the questions incorrectly.

In the year 2011, the estimated number of Medicare beneficiaries in the United States was approximately 50 million. According to the simulation results in Table 7.9, the average reduction in out-of-pocket expenditures per beneficiary when the information in each of the three categories is increased by one standard deviation is 30 dollars thus resulting in aggregate consumer savings of 1.50 billion dollars. At the same time, there is an increase in total medical expenditures of 432 dollars per beneficiary as a result of the greater information; thereby, increasing total Medicare spending by 21.60 billion dollars. Even after accounting for the consumer savings, there is an aggregate increase in health care spending of 20.10 billion dollars. While evaluating the impact

[8]The overall impact on health outcomes for the entire population is much smaller than the impact on individuals with functional limitations. However, this does not imply that the subgroup impact of information for the healthy individuals is negative as the percentage of individuals with functional limitations is relatively small (22 per cent).

Table 7.7: Five Year Simulations of Medical Expenditures and Health Outcomes under Full and No Information

	Full Information	No Information	Percentage Change	
Medical care expenditures				
Expenditures on inpatient services	9145.50	8934.42	2.30	(0.94)
Expenditures on outpatient and drug events	9967.87	9178.34	7.90	(2.17)
Total expenditures	19113.37	18112.76	5.24	(1.65)
Out-of-pocket expenditures	1916.53	2079.33	-8.50	(1.87)
Health outcomes				
Not disabled	75.88	73.25	2.63	(1.20)
Moderately disabled	16.62	17.14	-0.52	(0.53)
Severely disabled	7.50	9.61	-2.11	(1.14)
Above average self-reported health	40.91	38.86	2.05	(1.84)
Health outcomes of the disabled (22%)				
Not disabled	51.73	40.75	10.98	(0.56)
Moderately disabled	26.88	34.58	-7.70	(0.69)
Severely disabled	21.39	24.67	-3.28	(1.47)

Bootstrapped standard errors are provided in parantheses. Full Information: All individuals answer all the questions correctly. No Information: All individuals answer all the questions incorrectly.

of greater information, this increase in medical care spending has to be weighed against the improvement in health status of individuals with functional limitations. This positive impact can be measured by the increase in the percentage of moderately and severely disabled individuals who manage to transition into a 'no functional limitation' state. For a one standard deviation increase in information, this percentage change is approximately 2 per cent.

7.3 Relating the Findings to the Existing Literature

The primary contribution of this research is to examine the impact of imperfect information on insurance selection while allowing the plan choice to affect subsequent medical care utilization and evolution of health outcomes. Results show that information affects insurance choice and, in particular, more informed individuals are likely to choose 'greater' coverage (in the form of a Medicare Advantage Plan or by supplementing FFS Medicare with a Part D plan or a supplemental insurance plan). With the higher coverage associated with greater information, medical care utilization, particularly of the more discretionary types of care — preventive care, outpatient care, and prescription drugs — increases. Overall, at the level of the population, there are no significant

Table 7.8: Increasing Information Variables by One Standard Deviation, Each Period over Five Years: Insurance and Preventive Care Choice

	Simulated	One Std. Dev. Increase	Percentage Change	
Insurance Choice				
Medicare Advantage	36.86	40.34	3.48	(1.22)
Prescription Drug Plan	62.48	66.71	4.23	(1.86)
Supplemental Insurance	67.81	69.35	1.54	(1.37)
Preventive Care Choice				
Preventive Care	86.37	87.81	1.44	(0.75)

Bootstrapped standard errors are provided in parantheses.

health improvements but certain subgroups such as those who start in poor health realize gains in terms of health. This result is very similar to the findings of the predominant literature that has examined the relationship between insurance selection and medical care utilization such as The Rand Health Insurance Experiment (Manning et al., 1987), and more recently, The Oregon Health Insurance Experiment (Finkelstein et al., 2011). Both these studies randomize insurance coverage and find that insured individuals are more likely to consume medical care but gains in health as a result of the increased medical care utilization are confined to some sub-groups only.

With respect to the role of information frictions for individual out-of-pocket expenditures, this research finds that greater information leads to lower out-of-pocket expenditures, even after consuming higher levels of medical care, thus providing evidence that consumers with more information make relatively efficient plan choices. This result is also consistent with the huge strand of literature on information frictions such as Lin and Wildenbeest (2013); Ho et al. (2015), which find substantial gains for consumers when information frictions are removed.

7.4 Discussion of Equilibrium Effects

The simulation experiments above show that individuals acquiring more information incur lower out-of-pocket expenditures and improved health outcomes under certain conditions. These findings suggest that policies that reduce information frictions will enhance consumer welfare. However, this research does not model the supply side of the health insurance market (i.e., the

Table 7.9: Increasing Information Variables by One Standard Deviation, Each Period over Five Years: Medical Expenditures and Health Outcomes

	Simulated	One Std. Dev. Increase	Percentage Change	
Medical care expenditures				
Expenditures on inpatient services	9178.00	9271.00	1.03	(0.72)
Expenditures on outpatient and drug events	9880.34	10219.27	3.43	(1.69)
Total expenditures	19058.34	19490.27	2.26	(1.82)
Out-of-pocket expenditures	2140.79	2110.61	-1.43	(0.85)
Health outcomes				
Not disabled	70.81	69.33	1.48	(1.88)
Moderately disabled	18.02	18.67	-0.65	(1.24)
Severely disabled	11.17	12	0.83	(1.19)
Above average self-reported health	37.16	38.87	1.71	(0.73)
Health outcomes of the disabled (22%)				
Not disabled	49.25	51.24	1.99	(0.76)
Moderately disabled	27.95	26.14	-1.81	(1.05)
Severely disabled	22.8	22.62	-0.18	(1.18)

Bootstrapped standard errors are provided in parantheses.

effect of reducing information frictions on insurer pricing).[9] In this section, I draw upon existing literature to discuss the possible equilibrium effects of an increase in information in the population.

Compared to the market for private health insurance, Medicare is highly regulated even with respect to Medicare Advantage and Prescription Drug Plans, which are offered through private insurers, thus limiting the role of insurer practices for the effects of greater information among the consumers. In the market for Medigap, for example, (which are Medicare supplemental insurance plans), Lin and Wildenbeest (2013) find evidence for substantial consumer search costs and potential for consumer welfare through reduction in premiums when search costs are reduced. When consumer inattention is removed in the market for Prescription Drug Plans, Ho et al. (2015) find that effective insurer competition reduces premiums. The results from these empirical studies would suggest that the benefits of greater information, in terms of lower out of pocket expenditures, found in this research are a lower bound on the actual increase in consumer welfare. As consumers

[9]Modeling the supply side will make this complicated model of decision-making intractable. Moreover, data on insurer pricing is not available

become more informed and capable of making optimal decisions, premiums are expected to decrease too, resulting in more savings for the consumer.

However, just like other insurance markets, the market for health insurance also faces challenges like adverse selection and moral hazard. Imperfect information and inattention among consumers could be mitigating these problems to some extent. For example, consumers who are not aware of the characteristics of their insurance plans (such as deductibles) may not be responsive to the decrease in marginal prices caused by reaching the plan deductible thus reducing ex-post moral hazard. Some recent studies have corroborated this phenomenon. Handel (2013) shows that improved individual-level choices (due to reduced switching costs) substantially exacerbate adverse selection. When insurers take into account this increased adverse selection, premiums rise and there is an overall reduction in welfare. Handel (2013) uses data on insurance plans offered at a large firm in the US. Thus, the ultimate equilibrium impact of increased information among the elderly would depend on the extent of moral hazard and adverse selection in the Medicare health insurance market and the sensitivity of these phenomenon to consumer information.

While the equilibrium effects of information on out-of-pocket expenditures may be debatable, the positive effects on long-term health outcomes of the elderly through improved medical care choices should not be affected by the incorporation of insurer behavior in the model.

CHAPTER 8

CONCLUSION

This research constructs measures of individuals' information about their coverage choices using a previously unexploited survey component of the Medicare Current Beneficiary Survey, conducted by the Centers for Medicare and Medicaid Services, and examines the dynamic impact of imperfect information on insurance selection, medical care utilization, expenditure and health outcomes of the elderly by jointly estimating a set of theoretically derived dynamic demand and production functions. Several important, policy relevant findings come out of this analysis. First, informed individuals are more likely to choose Medicare Advantage Plans or supplement traditional fee-for-service Medicare with Prescription Drug Plans or some form of supplemental insurance. Second, simulation results suggest that greater information has welfare improving effects on the elderly population in terms of lower out-of-pocket expenditures and better long-term health outcomes for those with functional limitations. Third, while individuals benefit, total expenditures rise as the informed elderly consume more medical services including preventive care services than their less informed counterparts. These effects may be different with simulation over a longer time horizon when some health benefits could translate into cost savings for Medicare.

The simulation experiments also show that individuals in poor health status (having some functional limitations) realize an improvement in their health outcomes in addition to lower out-of-pocket expenditures. This finding suggests that policy makers should target limited resources for improving insurance literacy towards the subgroup of elderly with functional limitations.

The present analysis does not incorporate equilibrium effects of changes in insurer pricing strategies as individuals gain more information. Theoretical and empirical literature on information frictions shows that insurer mark-ups usually go down as frictions are removed from the market and consumers are able to make better decisions implying that the benefits of information estimated from this study, particularly, in terms of individual out-of-pocket savings, are a lower bound on the actual welfare effects of information. However, greater information and improved individual choices could also exacerbate phenomenon like adverse selection in health insurance markets leading to higher long-term prices (Handel, 2013).

By examining the determinants of imperfect information this research also helps identify some instruments through which policy makers could affect the information levels of Medicare beneficiaries. For example, even controlling for demographics such as education and income, information shifters such as 'having a personal computer at home' or 'receiving the Medicare and You book' have a strong, positive impact on the measure of individual information. These results suggest that the elderly are responsive to policies (such as public information campaigns, one-to-one counseling, initiatives to increase the outreach of the elderly to the internet) which are aimed at increasing their insurance literacy.

APPENDIX A

APPENDIX

A.1

The theoretical model described below captures the optimization problem of a rational agent who acquires costly information about the insurance plans available to her followed by the decision to enroll in a specific insurance plan and subsequent decision to purchase medical care in order to maximize the value of her lifetime utility in an environment where health is stochastic. Using this model, I derive a value function for information (equation 4.1 in Chapter 4) which is then used to specify an estimation equation.

Entering each period t, an individual agent knows her health condition, H_t, and her own demographic characteristics (e.g., education, income etc.), X_t. She may not know perfectly about the choice environment she is facing with regard to health insurance. She knows that the set of insurance alternatives include the 8 options (listed in Table 3.1).Let $\mathcal{I}$ be the set of insurance plans available to her. An insurance plan $I_t \in \mathcal{I}$ has price features $\mathbf{P}_t^I \equiv (P_t^I, P_t^{FI}, P_t^{MI})$, where F denotes preventive care services (e.g., mammograms, PSA tests, flu shots, routine eye check ups, etc.)[1] and M represents the medical care services. An insurance plan has an upfront cost (premium) captured by P_t^I. P_t^{FI} and P_t^{MI} denote the effective price of the medical care services covered by the insurance plan I. This effective price is determined by a plan's features including coverage, deductible, coinsurance, out of pocket maximum etc.[2] The agent does not perfectly know $\mathbf{P}_t^I$ and acquiring or processing this information is costly.

Let $\omega_t \in \Omega$ denote an underlying state at time t that determines the prices $\mathbf{P}_t(\omega_t)$. The agent has prior belief $\pi_t \in \Delta(\Omega)$ over the state. Let $\xi_t \in \Xi$ denote the signal received by the individual about the underlying state, where Ξ is a finite realization space, and $p(\xi_t|\omega_t)$ denote the probability

[1]These services do not include non-medical preventive care such as exercise, nutrition, relaxation etc.

[2]The effective price is defined very broadly- for example, one characteristic of an insurance plan could be the reputation of the seller. Ultimately, individuals are more likely to buy an insurance plan from an established seller because they expect that the effective price (taking into account the uncertainty of getting defrauded, payment delays etc.) is lower

of receiving signal ξ_t given that the state is ω_t. Then $\{p(.|\omega)\}$ (where '.' represents all possible ξ_t) is the probability distribution of signals given that ω is the underlying state. The set of distributions (or family of distributions), $\{p(.|\omega)\}_{\omega\in\Omega}$, captures the probability of each $\xi_t \in \Xi$ given any $\omega_t \in \Omega$. The set, $\{p(.|\omega)\}_{\omega\in\Omega}$, along with the signal space, Ξ, tells us everything we need to know about the probabilities of signal realizations and is referred to as the signal structure, Ξ_p.

For simplicity, we assume that $\Omega = \Xi = \{0,1\}^{|Q|}$, for some finite $|Q|$. Then, assuming that the probability of signal realizations for each of $(\omega_1, \omega_2, \ldots, \omega_{|Q|})$ are independent of each other and do not depend on the value of the actual state (i.e., do no depend on whether ω_k is 0 or 1), the signal structure can be represented by $p \equiv (p_1, p_2, \ldots p_{|Q|})$, where $p_{kt} := p(\xi_{kt} = \omega_{kt}|\omega_{kt})$. Thus, p_{kt} is the probability that the signal reveals the kth component of underlying state correctly. I will call this p the precision of the signals. The agent optimally chooses this p_t and incurs an acquiring and processing cost $\kappa(p_t)$ to do so.

The updated belief upon receiving signal ξ_t is

$$\pi'(\omega_t|\xi_t) = \frac{\pi_t(\omega_t)p(\xi_t|\omega_t)}{\sum_{\omega'_t} \pi_t(\omega'_t)p(\xi_t|\omega'_t)}$$

The posterior beliefs must be Bayes consistent, i.e.,

$$\sum_{\xi_t} p'(\xi_t)\pi'(\omega_t|\xi_i) = \pi_t(\omega_t)$$

Given this posterior belief, the agent's perception of the price environment is denoted by $\mathbf{P}_t^s(\xi_t)$, which is distribution over $\mathbf{P}_t(\omega_t)$. Thus, by choosing a signal structure, the agent receives signal ξ_t with probability $p'(\xi_t) = \sum_{\omega_t} \pi_t(\omega_t)p(\xi_t|\omega_t)$ and given the signal ξ_t, her price perception is $\mathbf{P}_t^s(\xi_t)$.

Timeline: The agent enters time t with state variables H_t, X_t, m_{t-1} and belief π_t. We include m_{t-1} as a state variable because there may be persistent effects in the use of medical care. The agent goes through the following decision making steps (depicted in the timeline in Figure 1).

1. At the beginning of time t, the agent chooses precision, $p_t \in P \equiv [0,1]$.

2. The agent receives a particular realization ξ_t from her chosen signal structure. Based on this realization and her prior, π_t, she forms her perception $\mathbf{P}_t^{Is}$, about actual price features $\mathbf{P}_t^{I}$.

3. Subsequently, the agent evaluates insurance alternative, $I \in \mathcal{I}$ based on her health, H_t, individual characteristics, past medical care, m_{t-1}, X_t, perception $\mathbf{P}_t^s \equiv (\mathbf{P}_t^{Is})_{I\in\mathcal{I}}$

4. After selecting an insurance plan, she decides whether or not to consume preventive care $f_t \in F_t$.

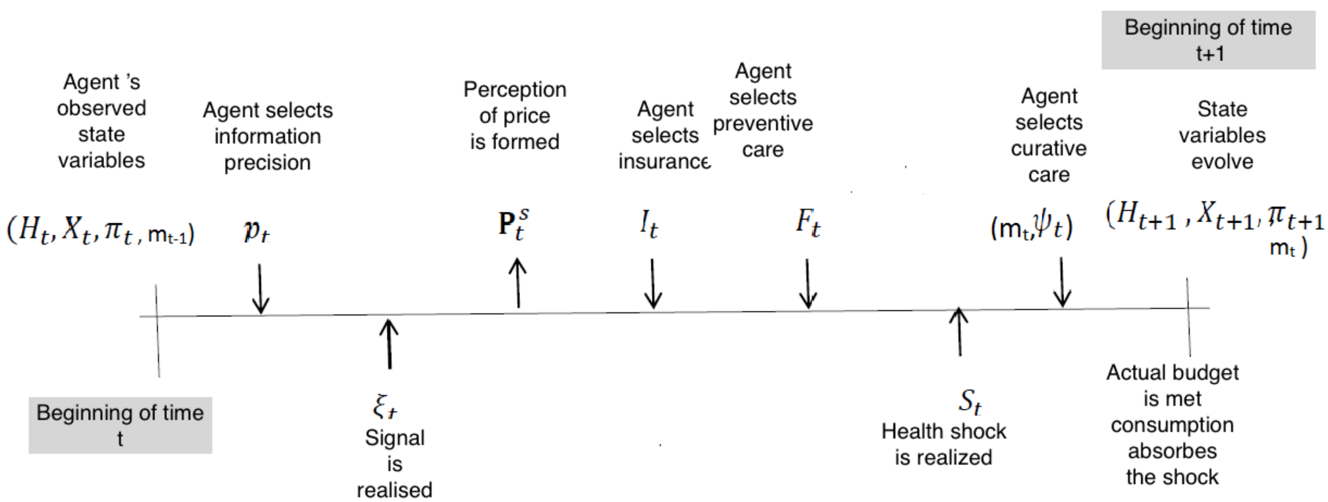

Figure A.1: Timing of the Model

5. After the preventive care decision, uncertain health shocks within the period are realized, $S_t \in \mathcal{S}_t$.

6. Depending on the shock realized and conditional on the other previous decisions (I_t and f_t), the individual chooses her medical care consumption, m_t.

7. Health evolves, such that health entering the next period, H_{t+1}, is a function of current health, H_t, the health shock, S_t, and medical care inputs (f_t, m_t).

8. The updated belief $\pi_{t+1} = \pi_t'(\xi_t)$.

Within each period, the consumer derives utility from consumption (C_t) and health (H_t). We abstract from the labor-leisure decision because most respondents are above age 65. Per period utility is described by:

$$U_t = U(C_t, H_t)$$

The individual allocates income between a composite consumption good, insurance, and medical care inputs. The budget constraint of the individual is represented by:

$$Y_t = C_t + \mathbf{P}_t^I.(I_t, f_t, m_t)$$

where Y_t is income and C_t is a composite consumption good with price normalized to 1. P_t^I is the price of insurance of plan I and other P_t variables (P_t^{FI}, P_t^{MI}) denote the actual effective price of medical services when insurance plan I_t is chosen in period t.

Health in next period is determined by health entering the period, health shocks, medical care inputs chosen in the period and demographic variables. If we discretize health into $h = 1, \ldots H$ categories, then:

$$\Pr(H_{t+1} = h) = f^h(H_t, X_t, f_t, S_t, m_t), \quad h = 1, ..., H$$

The probability of health shocks (S_t) is a function of the state variables entering period t and the preventive care chosen in period t

$$\Pr(S_t = 1) = g^S(H_t, X_t, F_t)$$

This individual is observed for a finite, T, periods in the data. The objective of the individual is to choose the precision with which to know the price environment, type of insurance coverage and the levels of medical care inputs (preventive and curative) that maximize her lifetime utility. The decision to acquire information, the health insurance choice, and the use of preventive care services is made prior to the realization of the health shock, and the choice of curative medical inputs is made after the realization of the shock.

We can represent the individual's decision making problem using a Bellman equation. We begin with the last decision of the period, the curative medical care decision. The perceived value of lifetime utility of choosing $m_t \in M_t$ at time t, conditional on the choice of insurance (I_t), the preventive care utilization (F_t), the health shock (S_t) and the preference error term (u^M_{mt}) for each t<T is

$$V^M_{mt}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t), u^M_{mt}|p_t, I_t, F_t, S_t) = E_{\pi'(\omega_t|\xi_t)}U(Y_t - {P_t}^I(\omega_t)I_t - {P_t}^{FI}(\omega_t)F_t - {P_t}^{mI}(\omega_t)m_t, H_t) + u^M_{mt} + \beta(\sum_{h=1}^{H}\Pr(H_{t+1} = h|H_t, X_t, F_t, S_t, m_t)V_{t+1}(H_{t+1}, X_{t+1}, m_t, \pi_{t+1}) \quad \text{(A.1)}$$

and for t=T

$$V^M_{mt}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t), u^M_{mt}|p_t, I_t, F_t, S_t) = E_{\pi'(\omega_t|\xi_t)}U(Y_t - {P_t}^I(\omega_t)I_t - {P_t}^{FI}(\omega_t)F_t - {P_t}^{mI}(\omega_t)m_t, H_t) + u^M_{mt} + \beta(\sum_{h=1}^{H}\Pr(H_{t+1} = h|H_t, X_t, F_t, S_t, m_t)Q_{t+1}(H_{t+1}, X_{t+1}, m_t, \pi_{t+1}) \quad \text{(A.2)}$$

where Q_{T+1} is the value of expected discounted future utility at the end of year T which is approximated by a closing function, i.e., I assume that this value is determined by a non-stochastic (i.e., no error term) linear function of the state variables entering the first period after T, medical care consumed in T, and a vector of parameters.

Note that agents makes their choice based on their perception $\mathbf{P}^s_t$,[3] but after the health choices have been made the actual cost depends on the actual prices. I assume actual consumption is the residual budget, i.e. the agent cannot make adjustment to his health consumption further to meet

[3] I do not assume that once an insurance plan is chosen, all its characteristics are automatically revealed to the individual

his budget.[4] Due to imperfect information, the agent may be mistaken about the value of this residual budget. Thus, she makes an optimization error.

Having defined $V^M_{mt}(H_t, X_t, m_{t-1}\pi_t, \mathbf{P}^s_t(\xi_t), u^M_{mt}|p_t, I_t, F_t, S_t)$, we can now consider the preventive care decision. At the time of preventive care selection, S_t is not known. The value of each preventive care alternative f, unconditional on curative care decision but conditional on choice of insurance and preventive care decision is given by

$$V^F_{ft}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t), u^F_{ft}|p_t, I_t) =$$
$$\sum_{s=1}^{S} P(S_t = s) E_{u^M_t}[\max_m V^M_{mt}(H_t, X_t, m_{t-1}\pi_t, \mathbf{P}^s_t(\xi_t), u^M_{mt}|p_t, I_t, F_t, S_t)] + u^F_{ft} \quad \text{(A.3)}$$

The maximal expected lifetime utility unconditional on preventive care choice but conditional on insurance choice is

$$V^{\mathcal{I}}_{It}(H_t, X_t, m_{t-1}\pi_t, \boldsymbol{P}^s_t(\xi_t), u^{\mathcal{I}}_{It}|p_t) = E_{u^F_t}[\max_f V^F_{ft}(H_t, X_t, m_{t-1}, \pi_t, \boldsymbol{P}^s_t(\xi_t), u^F_{ft}|p_t, I_t)] + u^{\mathcal{I}}_{It} \quad \text{(A.4)}$$

Note that the value function in equation A.4 is still conditional on the selected precision of information, p_t. The value of a choice of p is

$$V^P_{pt}(H_t, X_t, m_{t-1}, \pi_t) = E_{u^{\mathcal{I}}_t}\left[\max_I V^{\mathcal{I}}_{It}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t), u^{\mathcal{I}}_{It}|p_t)\right] \quad \text{(A.5)}$$

Finally, given the cost of p_t, $\kappa(p_t)$, the value function right at the beginning of time t and before making any choices is

$$V_t(H_t, X_t, m_{t-1}, \pi_t) := \left[max_{p_t} E_{p'(\xi_t)} V^p_t(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t)) - \kappa(p_t)\right] \quad \text{(A.6)}$$

To understand the value of information, notice that under complete information (i.e. when

[4]See Gabaix, 2014Gabaix (2011) for sparse maximization when agents make income adjustment in case they fail to meet budget. Another way to avoid this income adjustment will be to assume quasi linear preference.

$p_t = \mathbf{1}$), the individual will choose her insurance plan according to $\phi_c : \Omega \to \mathcal{I}$, where

$$\phi_c(\omega_t, .) := \arg\max_{I \in \mathcal{I}} V^{\mathcal{I}}_{It}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}_t(\omega_t), u^{\mathcal{I}}_{It}|\mathbf{1})$$

Recall that

$$V^{\mathbf{1}}_t(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}_t(\omega_t)) = E_{u^{\mathcal{I}}_t} \max_{I \in \mathcal{I}} V^{\mathcal{I}}_{It}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}_t(\omega_t), u^{\mathcal{I}}_{It}|\mathbf{1})$$

Now suppose the agents do not have full information. Let $\phi_c(\omega)$ denote the *right* choice and $\phi'_c(\omega)$ denote the *wrong* choice when state is ω. The agent chooses a precision $p_t < 1$. Based on the signal realization, she makes her choice $\phi : \Xi \to \mathcal{I}$, where

$$\phi(\xi_t|p_t, .) := \arg\max_{I \in \mathcal{I}} V^{\mathcal{I}}_{it}(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t), u^{\mathcal{I}}_{It}|p_t, I_t) \tag{A.7}$$

Definition 1 *Given an underlying state ω , and signal realization ξ, the agent makes a **Mistake** if $\phi(\xi|p, .) \neq \phi_c(\omega, .)$*

Let us define $\mathcal{M}(\omega|p) := \{\xi : \phi(\xi|p) \neq \phi_c(\omega)\}$ as the set of signal realizations for which the individual would have made a mistake, had the state been ω. Define the complementary set as $\mathcal{M}'(\omega|p)$. Consider any $\xi \in \mathcal{M}(\omega|p)$, the individual chooses $\phi(\xi|p) \neq \phi_c(\omega)$. Thus, had the actual underlying state been ω the agent would have a welfare loss defined by

$$V^{\mathbf{1}}_t(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}_t(\omega_t)) - V^{p}_t(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t))$$

Therefore, given signal Ξ_{p_t}, prior π_t and H_t, X_t, the total utility loss at state ω is

$$L(\omega|H_t, X_t, m_{t-1}, \pi_t, p_t) = \sum_{\xi \in \mathcal{M}(\omega|p)} \left[V^{\mathbf{1}}_t(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}_t(\omega_t)) - V^{p}_t(H_t, X_t, m_{t-1}, \pi_t, \mathbf{P}^s_t(\xi_t))\right] p(\xi_t|\omega_t) \tag{A.8}$$

Therefore, the total loss from choosing $p_t < 1$ is

$$L(H_t, X_t, m_{t-1}, \pi_t, p_t) = \sum_{\omega \in \Omega} L(\omega | H_t, X_t, m_{t-1}, \pi_t, p_t) \pi_t(\omega) \tag{A.9}$$

The individual chooses p to minimize the value of this loss plus the cost $\kappa(p)$ which is equivalent to maximizing the RHS in equation A.5.

A.2

The Beneficiary Needs and Knowledge supplement of the Medicare Current Beneficiary Survey (MCBS) reports respondents' knowledge about their insurance choice set through a series of questions which allow for 'yes', 'no' or 'don't know' responses (listed below). I categorize the questions into three categories: questions related to Medicare Advantage Plans (Q^{MA}), questions related to Prescription Drug Plans (Q^{PDP}) and questions related to coverage of preventive care services through Medicare (Q^{PREV}).[5] There is a correct answer to each of these questions forming a profile of correct answers (analogous to the underlying state of the world $\Omega = \Xi = \{0,1\}^{|Q|}$ in the theoretical model described in section A1 of the Appendix). The responses given by the beneficiaries to these questions form their perceptions about the effective price (analogous to $\mathbf{P}_t^s \equiv (\mathbf{P}_t^{Is})_{I \in \mathcal{I}}$ in the theoretical model) faced by them with respect to each of the insurance options. For example, consider the first question - 'Do Medicare Advantage plans usually cover more services?'- The correct response to this question is 'yes'. The beneficiary who knows gives the response 'yes' to this question would realize (correctly) that the effective price of coverage through Medicare Advantage plans based on this question is lower, ceteris paribus.

$$Q^{MA} = \begin{cases} \text{Do Medicare Advantage plans usually cover more services?} \\ \text{If the Medicare HMO quits, Medicare will be covered by FFS?} \\ \text{Can Medicare HMO raise fees/change benefits each year?} \end{cases}$$

[5]The supplement has additional questions. The questions listed here are asked every year allowing us to construct a consistent measure of information through the years.

$$Q^{PDP} = \begin{cases} \text{Is limited income and resources assistance available for PDP?} \\ \text{Are out of pocket costs are the same for all drug plan?} \\ \text{Do all drug plans cover the same list of drugs?} \end{cases}$$

$$Q^{MPREV} = \begin{cases} \text{Does Medicare cover an annual mammogram for women?} \\ \text{Does Medicare cover an annual PSA test for men?} \\ \text{Does Medicare cover a routine dental exam?} \\ \text{Does Medicare cover annual flu shot?} \\ \text{Does Medicare cover colon cancer screening?} \\ \text{Does Medicare cover cardiovascular screening?} \\ \text{Does Medicare cover routine eye exam?} \\ \text{Does Medicare cover diabetes screening?} \end{cases}$$

As the econometrician, I do not directly observe the value of the precision chosen by the individual in the data. However, I observe the beneficiaries' responses to the above questions and I know the actual correct answers to these question in each time period. Based on these, I form the 'number of correct responses' for each individual in each time period which serve as a proxy for the value of p.[6] From now on, I will use the terms 'precision', 'information' and 'number of correct responses' interchangeably.

A.3

Data on the endogenous and exogenous variables in the first year when each individual is observed in the sample is used to get parameter estimates for initial condition equations specified below. I estimate seven initial condition equations[7] explaining, the functional status, the number

[6] It is intuitive to think of the precision choice as the choice of 'effort' exerted by the individual in collecting information and the actual number of correct responses given by the individual as a function of that effort as well as other factors like cognitive ability. However, the only distinction between the two is in terms of unobservables (like cognitive ability) which I control for by modeling the unobserved heterogeneity.

[7] Initial conditions are are estimated for each endogenous state variable and initially observed health insurance choice.

of chronic conditions, the self-reported health, three equations for the choice of insurance plan and the end of period total medical expenditure of the individual.

The probability of observing the choice of a MA/PDP/Supplemental Insurance plan in the initial period is given by:

$$ln\left[\frac{\Pr(I_0^j=1)}{\Pr(I_0^j=0)}\right]=\gamma_{0j}^1+\gamma_{1j}^1X_t+\gamma_{2j}^1Z_0^{\mathcal{I}}+\gamma_{3j}^1Z_0^M+\gamma_{4j}^1Z_0^H+\gamma_{5j}^1t+\gamma_{6j}^1t^2+\mu_0^{j\mathcal{I}} \tag{A.10}$$

where j= MA, PDP, SUPP

The initial number of severity adjusted chronic conditions is modeled as:

$$R_0=\gamma_0^2+\gamma_1^2X_t+\gamma_2^2Z_0^H+\gamma_6^2t+\gamma_7^2t^2+\mu_0^R \tag{A.11}$$

Log use of total medical care expenditures in the first period of observation are modeled as:

$$E_0=\gamma_0^3+\gamma_1^3X_t+\gamma_2^3I_0^{MA}+\gamma_3^3I_0^{PDP}+\gamma_4^3I_0^{SUPP}+\gamma_5^3Z_0^M+\gamma_6^3Z_0^H+\gamma_7^3R_0+\gamma_8^3t+\gamma_9^3t^2+\mu_0^E \tag{A.12}$$

The probability of initially observed functional status is

$$ln\left[\frac{\Pr(L_{t+1}=a)}{\Pr(L_{t+1}=0)}\right]=\gamma_{0a}^4+\gamma_{1a}^4X_t+\gamma_{2a}^4E_0+\gamma_{3a}^4Z_0^H+\mu_0^{aH} \tag{A.13}$$

where a=(1,2), and the initial self-reported health is given by the following estimation equation

$$G_0=\gamma_0^5+\gamma_1^5X_t+\gamma_2^5Z_0^H+\gamma_6^5t+\gamma_7^2t^2+\mu_0^G \tag{A.14}$$

Z_0^H includes height of the individual which proxies for health during childhood and the median air quality index of her area of residence. Time varying heterogeneity does not enter the equation for the initial state variables because these variables summarize the history of behavior and outcomes from all periods prior to inclusion in the survey sample.

A.4

The likelihood function is:

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