Insurance-Induced Moral Hazard: A Dynamic Model of Within-Year Medical Care Decision Making Under Uncertainty*

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Abstract

Insurance-induced moral hazard may lead individuals to overconsume medical care. Many studies estimate this overconsumption using models that aggregate medical care decisions up to the annual level. Using employer-employee matched data from the Medical Expenditure Panel Survey (MEPS), I estimate the effect of moral hazard on medical care expenditure using a dynamic model of within-year medical care consumption that allows for endogenous health transitions, variation in medical care prices, and individual uncertainty within a health insurance year. I then calculate moral hazard effects under a second set of conditions that are consistent with the assumptions of most annual decision-making models. The within-year decision-making model produces a moral hazard effect that is 24% larger than the alternative model. I also provide evidence of heterogeneous moral hazard effects, particularly between insured and uninsured individuals, and discuss related policy implications. The paper concludes with a counterfactual policy simulation that implements the individual mandate provision of the 2010 Patient Protection and Affordable Care Act. I find that full implementation of the individual mandate decreases the percentage of uninsured individuals in the population being analyzed from 11.8% to 6.0% and increases average medical care expenditure 77% among the newly insured.

JEL Classification: C61, D81, G22, I12, I13

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1 Introduction

Economic theory suggests that health insurance may increase medical care consumption above the socially optimal level (Arrow, 1963; Pauly, 1968). The incentives that elicit this increase in consumption are often referred to as moral hazard (Cutler and Zeckhauser, 2000).[1] Empirical studies tend to estimate moral hazard effects using models that aggregate medical care decisions up to the annual level. In this paper, I study insurance-induced moral hazard using a dynamic stochastic model of within-year medical care consumption decisions. The within-year decision-making model more accurately captures the data generating process by relaxing several assumptions made frequently in the literature. Specifically, the model allows for endogenous health transitions, variation in medical care prices, and individual uncertainty within a health insurance year. The paper contributes to the literature in two ways. First, I show that the within-year decision-making model produces a moral hazard effect that is 24% larger than an alternative model that imposes the more restrictive assumptions of a typical annual expenditure model.[2] Second, I provide evidence of heterogeneous moral hazard effects, particularly between insured and uninsured individuals. I explain why each of these findings is consistent with economic theory and show how differences in estimated moral hazard effects can lead to large differences in predicted policy outcomes. I also conduct a series of counterfactual policy simulations to study the potential effects of the individual insurance mandate provision of the 2010 Patient Protection and Affordable Care Act (ACA).

The within-year decision-making model is motivated by theoretical (Grossman, 1972; Keeler et al., 1977) and empirical (Gilleskie, 1998; Cardon and Hendel, 2001; Khwaja, 2001, 2010; Blau and Gilleskie, 2008) models of health production and medical care demand. An individual's optimization problem consists of an annual health insurance decision, followed by a sequence of monthly medical care consumption decisions made over the course of a health insurance year. I model monthly medical care decisions to allow the unique benefits and costs associated with the

[1] The term *moral hazard* is used rather loosely in the health economics literature. I describe moral hazard as the incentives associated with insurance possession that lead to changes in individual behavior. I focus on one effect of moral hazard, which is the effect that health insurance possession has on medical care consumption. I also discuss the welfare implications of this additional consumption.

[2] The moral hazard effect is measured as the percentage increase in mean annual medical care expenditure that is caused by insurance acquisition. A more detailed description of this calculation is given in Section 6.3.

timing of unexpected illness and potential medical care consumption to impact behavior within the model. Within each month, a forward-looking individual responds to an endogenous stochastic health event by consuming units of medical care. The (anticipated) primary benefit of medical care consumption is improved future health. The (anticipated) primary cost is financial (i.e., a decrease in the current consumption of non-medical goods).[3] When health insurance has dynamic cost-sharing features (i.e., deductible and stop loss), an additional benefit of current medical care consumption is the reduced cost of future care once accumulated expenditure crosses a threshold.[4] The model also allows a direct contemporaneous utility benefit or cost of medical care consumption that is independent of the productive and financial effects.

An individual faces uncertainty along multiple dimensions of the optimization problem. Prior to both an annual health insurance decision and each monthly medical care decision, an individual is uncertain of his future health outcomes, medical care consumption, and medical care prices. Furthermore, I assume that prior to medical care consumption an individual knows the conditional distributions from which medical care prices are drawn, but does not know the exact prices he will be charged for different types of care.[5] Though it is typically assumed that prices are known prior to consumption, there are several reasons why price uncertainty is a more realistic assumption. First, an individual rarely knows a physician's diagnosis and recommended treatment prior to an office or hospital visit. Second, in the U.S., medical care providers do not display a menu of prices and there is evidence of wide price variation in local medical care markets. Each of these market characteristics make it difficult for an individual to know exactly how much he will be charged for care.

The within-year decision-making model, which is characterized by these important market fea-

[3] I qualify *anticipated* benefits and costs because the estimated model parameters determine both the sign and magnitude of medical care productivity (in producing positive health outcomes) and the disutility from reduced consumption of non-medical goods. I expect to find that medical care is productive, a reduction in non-medical consumption yields disutility, and that each plays a principle role in the medical care decision-making process.

[4] A deductible is a fixed amount of accumulated medical care expenditure that must be reached (within an insurance year) before the insurer covers any part of total medical care costs. A stop loss is an accumulated out-of-pocket expenditure threshold at which an individual's share of the total cost of any additional medical care consumed during that insurance year is zero.

[5] I use the terms *price* and *total cost*, interchangeably, to describe the total amount billed for a unit of medical care. The *out-of-pocket cost* to an individual is often less than the price billed due to insurance cost-sharing. The difference between medical care prices and costs paid out-of-pocket is discussed further in Section 3.4.

tures, also has several empirical advantages. First, the model has the ability to capture patterns in the data that are explained by within-year behavior. For example, in the estimation sample, average monthly medical care expenditure is \$127.60 higher in months where an individual has an acute illness. This spending gap exists even when conditioning on chronic illness entering the year: expenditure is \$119.78 higher in acute illness months for those without a chronic illness and \$140.30 higher for those with a chronic illness.[6] This behavior can be explained by the within-year decision-making model if medical care decreases the likelihood of having an acute illness and has a financial cost. Second, the assumptions imposed on the within-year decision-making model may impact the estimated effect of moral hazard. For example, the model allows medical care consumption to affect health over the course of a health insurance year (i.e., within-year health transitions are treated as endogenous). Most models of medical care demand either do not model health at all (implicitly assuming that health transitions are exogenously determined) or model annual health outcomes. Allowing for endogenous health transitions within an insurance year impacts the estimated effect of moral hazard if the insured consume more medical care but then find themselves in better health, decreasing the need for medical care consumption in the future.

I estimate the model parameters via maximum likelihood using employer-employee match data from the 1996-1999 Medical Expenditure Panel Survey (MEPS). I use simulation techniques to examine model fit and to calculate the effect of moral hazard on medical care expenditure. I conduct a set of counterfactual simulations to study how different assumptions imposed on a within-year decision-making model lead to different moral hazard effects. Specifically, I examine how the estimated effect of moral hazard responds to the assumption that health transitions are exogenously determined (assumption 1), that medical care prices are known prior to consumption (assumption 2), and that all health and price shocks are known at the beginning of the year (assumption 3). The main counterfactual imposes assumptions 1, 2, and 3, as these assumptions are consistent with those made implicitly in most annual expenditure models, such as Cardon and Hendel (2001), Einav et al. (2013), and Kowalski (2013).[7]

[6]Throughout the paper, all dollar amounts are reported in 1996 dollars, unless stated otherwise.

[7]Bajari et al. (2013) is similar but does allow for some uncertainty at the time of medical care decision making. The authors assume that an individual selects his total annual medical care expenditure while knowing only the distribution of the proportion of that expenditure he must pay out-of-pocket.

Health insurance acquisition is predicted to increase mean annual medical care expenditure by 92% using the (preferred) within-year decision-making model and 74% when assumptions 1, 2, and 3 are imposed. The counterfactual estimate compares favorably with estimates produced by several annual expenditure models in the literature.[8] Ultimately, the presence of health and price uncertainty at the time of medical care consumption in the preferred model decreases the expected value of medical care consumption. The larger moral hazard effect produced by the within-year model is driven by exceptionally low medical care consumption when uninsured, as risk averse individuals who face uncertainty are exposed to significant risk in consumption.

I find heterogeneous moral hazard effects across the population. The 92% increase in mean annual medical care expenditure that results from insurance acquisition is driven by individuals with exceptionally large increases in expenditure. If the top 1% of additional spenders are dropped, then the increase in mean expenditure due to insurance is reduced to 65%. Furthermore, 44% of the population does not increase their expenditure at all when they become insured. I also find significant differences in how insured and uninsured individuals respond to coverage. When individuals are moved from an uninsured state to their optimal plan, mean annual medical care expenditure in the insured population increases by 96%; however, mean annual medical care expenditure in the uninsured population increases by only 55%. In Section 6.3.2, I discuss the factors that drive these differences and explore the policy implications of the differential response to coverage between these two groups.

The paper concludes with a counterfactual exercise that examines the behavioral response to an individual insurance mandate that is consistent with the ACA.[9] When facing a penalty of $695 (in 2016 dollars) or 2.5% of income (whichever is larger) for failing to carry health insurance coverage, the proportion of the population being analyzed that chooses to be uninsured decreases from 11.8% to 6.0%. Of the previously uninsured population, mean annual medical care expenditure for the newly insured increases by 77% (moral hazard effect), while expenditure for those remaining

[8]Differences in estimation samples, insurance offer sets, and reported measures of moral hazard effects make it difficult to compare estimates across papers. Attempts are made to draw such comparisons in Section 6.3.

[9]This counterfactual implements the individual mandate provision of the ACA only. There are many other regulations that the ACA imposes upon the marketplace that are not considered. Furthermore, the empirical analysis conducted in this paper focuses on a population of individuals who are unmarried, childless, employed, between the ages of 19 and 64, and have the ability to purchase health insurance through their employers.

uninsured falls by 2.4% (income/penalty effect). Given that the full implementation penalty does not elicit universal coverage, I also examine the welfare implications of forced insurance take-up. Holding insurance premiums and medical care prices fixed, I find that among uninsured individuals the average expected welfare loss from forced take-up is $1608 (2016 dollars).[10]

The following section provides motivation for this research and discusses some of the previous literature. Section 3 details the theoretical model of insurance and within-year medical care demand. Section 4 describes the data and the sample used in estimation. Section 5 details the estimation procedure and discusses identification. Sections 6 presents preliminary parameter estimates, model fit, and counterfactual simulations. Section 7 concludes.

2 Motivation and Background

Health insurance generates welfare by protecting risk averse individuals from medical expenses associated with unforeseen health shocks (Arrow, 1963). However, the welfare gains from risk protection are potentially mitigated by changes in individual behavior after becoming insured. For example, insurance lowers the out-of-pocket cost of medical care, which can lead to excess consumption when sick, known as ex-post moral hazard (Pauly, 1968). Also, a reduction in the expected cost of curative medical care can reduce participation in healthy behaviors (e.g., preventative medical care, diet, exercise, etc.) leading to worse health outcomes and potentially greater medical care consumption in the future, known as ex-ante moral hazard (Cutler and Zeckhauser, 2000). Each of these forces drives insured individuals to consume medical care past the socially optimal level, generating a welfare loss.[11] Therefore, efficient health insurance plan design requires an understanding of how health insurance leads to changes in individual medical care consumption behavior.

[10]The average expected welfare loss is measured as the average penalty that would make an uninsured individual indifferent between remaining uninsured and paying the penalty or being insured and paying the premium.

[11]It is assumed here that the level of medical care consumption when uninsured is socially optimal. If medical care prices are non-competitive or if their are externalities in medical care consumption (e.g., the reduction of communicative diseases), then consumption when uninsured may not be efficient. Even if the level of consumption when uninsured is socially optimal, it is not the case that the full increase in medical care consumption due to insurance acquisition is welfare reducing. As is covered extensively by Nyman (1999a,b,c), the additional medical care consumption that is caused by insurance possession results from both lower out-of-pocket medical care costs and an income transfer from the well to the sick, the latter of which is welfare neutral. The main moral hazard effect discussed in this paper includes the income effect, because there are no welfare calculations presented at this time. Planned welfare experiments, some of which are discussed in the web appendix, account for this income transfer.

Determining how medical care consumption and welfare are affected by health insurance has been a central focus of empirical health insurance and medical care research over the past 30 years. The primary challenge in estimating, for instance, the percentage increase in mean annual medical care expenditure that is caused by health insurance possession (i.e., a measure of the effect of moral hazard) is the endogenous selection of health insurance. Those who expect to consume more medical care during a health insurance year select generous health insurance coverage; this is known as adverse selection (Akerlof, 1970).[12] Both moral hazard and adverse selection lead to a positive correlation between observed medical care expenditure and insurance possession/generosity;[13] however, the extent to which this correlation is driven by moral hazard or adverse selection has important policy implications.[14]

One method that has been used to control for endogenous insurance selection, so that moral hazard effects can be identified, is a randomized experiment. A well known example is the RAND Health Insurance Experiment (HIE). The 1971 RAND HIE was a multi-year, $295 million (in 2011 dollars, (Greenberg and Shroder, 2004)) medical care study that, among other things, randomly distributed health insurance plans to participants in 6 U.S. cities and recorded health and medical care consumption in the years following (for more details, see Newhouse, 1974, 1993). By randomly assigning coverage, the experiment's design created exogenous variation in insurance holdings so that price elasticities (i.e., another measure of the effect of moral hazard) could be estimated. A more recent example of researchers using experimental data to study moral hazard is the Oregon HIE. In 2008, the Oregon Health Authority expanded the state's Medicaid program to 10,000

[12] When private information (e.g., risk aversion) leads low risk/expenditure types to purchase more comprehensive health insurance the behavior is known as advantageous selection (de Meza and Webb, 2001; Finkelstein and McGarry, 2006).

[13] In the empirical health economics literature, moral hazard normally refers only to ex-post moral hazard (some exceptions are Dave and Kaestner (2009) and Kelly and Markowitz (2009)). Ex-ante moral hazard is difficult to study for two reasons. First, ex-ante moral hazard involves changes in many non-medical behaviors (i.e., exercise, diet, smoking, etc.). Second, ex-ante moral hazard results from poor health behaviors that lead to worse health outcomes, meaning endogenous health transitions must be modeled. The model presented in this paper allows for ex-post moral hazard and limits the effect of ex-ante moral hazard to changes in medical care consumption. That is, an individual in the model may respond to health insurance coverage by consuming medical care less frequently, which may lead to poor health outcomes and greater medical care consumption in the future. However, I do not model non-medical behavioral responses to insurance acquisition.

[14] If moral hazard is the dominant force behind this correlation, then policy makers should encourage less risk protection through greater cost-sharing. Requiring an individual to pay a larger share of the price of medical care reduces his incentive to overconsume care. If adverse selection is the dominant force, then policy makers should encourage greater risk pooling.

additional low-income adults using a lottery (i.e., qualifying individuals were randomly selected and given the ability to apply for coverage). Again, random assignment allows these researchers to study moral hazard without concern for endogenous insurance selection. This experiment is ongoing, though one year (Finkelstein et al., 2012) and two year (Baicker et al., 2013) evaluations of the program have been published. There are also numerous quasi-experimental studies that use econometric techniques and exogenous (or near exogenous) shifts in insurance policy, such as Medicaid expansion (Currie and Gruber, 1996; Dafny and Gruber, 2005) or the Massachusetts market reforms (Miller, 2012; Kolstad and Kowalski, 2012), to control for adverse selection.

While both experimental and quasi-experimental techniques have been used to successfully control for adverse selection so that moral hazard effects may be identified, a principle goal in this literature is to move beyond measuring the spending response to observed plans and/or policies.[15] Recently, research efforts have focused on measuring the welfare implications of the additional spending caused by moral hazard and designing insurance plans and insurance plan alternative sets that improve consumer welfare. In this pursuit, researchers have turned to structural modeling.[16] Importantly, structural models have allowed researchers to both control for adverse selection in order to quantify moral hazard effects and to calculate the welfare implications of these effects. Furthermore, because insurance decisions are typically modeled and insurance cost-sharing characteristics are allowed to impact optimal medical care decision making through the budget constraint, the models are well suited to study behavioral and welfare responses to counterfactual insurance plans, insurance alternative sets, and regulatory policies.

[15] The experimental and quasi-experimental research found in this literature has generally focused on analyzing the effects of specific policies on outcomes of interest. Unfortunately, these results are difficult to generalize, as the estimated effects are normally applicable for only a specific policy and population. Manning et al. (1987) and Keeler and Rolph (1988) are exceptions to this rule, as they estimate a single price/co-insurance elasticity of medical care demand that is frequently used by researchers and policy makers to predict changes in medical care expenditure levels that would result from insurance plans and policies not observed in the marketplace. However, as is discussed extensively in Aron-Dine et al. (2013), application of the single price elasticity measure requires a researcher to characterize a health insurance plan by a single price. Because modern health insurance plans are characterized by many cost-sharing features that change the out-of-pocket cost of medical care over the course of a health insurance year, there is no obvious way to summarize a plan by a single price. Aron-Dine et al. (2013) conduct an empirical exercise where they predict medical care expenditure using the single price elasticity and implement several common strategies for determining a single price. Their results show wide variation in predicted results depending on the strategy used.

[16] In this context, structural modeling should be interpreted as explicitly modeling and estimating the parameters of an individual's optimization problem with regard to medical care consumption. See Chiappori and Salanie (2002) and Einav et al. (2010) for a review of this technique.

Among the related structural models that have been designed and estimated (Cardon and Hendel, 2001; Khwaja, 2001, 2010; Einav et al., 2013; Kowalski, 2013; Bajari et al., 2013; Handel, 2013), all have aggregated medical care expenditures and health outcomes up to the annual level.[17] Annual expenditure models have been popular, here and elsewhere in the health economics literature, primarily due to data limitations. Annual medical care expenditure data are accessible. Large public data sets, which contain total annual expenditure variables that have been cleaned and are ready for immediate use, are used by many empirical researchers and allow for nationally representative findings.[18] Also, estimation of annual expenditure models can be achieved without high frequency explanatory data, such as illness state, which is both difficult to find and desirable when estimating a model of within-year medical care decisions.[19] My research builds on these structural annual expenditure models by allowing for monthly medical care consumption decisions to be made over a health insurance year and by relaxing several assumptions commonly made in annual decision-making models.[20]

3 Model

The model described in this section captures the optimization problem of an unmarried, childless, employed individual who makes an annual health insurance decision followed by a sequence of med-

[17]Khwaja (2001, 2010) aggregates to the biennial level.

[18]Examples are: the Medical Expenditure Panel Survey (MEPS); the Health and Retirement Survey (HRS), which has been cleaned by RAND; and the Medicare Current Beneficiary Survey (MCBS).

[19]Note that while insurer claims data (or claims data from a large self-insuring company, which are used in Einav et al., 2013; Kowalski, 2013; Bajari et al., 2013; and Handel, 2013) allow for the observation of high-frequency medical care consumption decisions, illness state is only observed when an individual chooses to consume care. Therefore, endogenous health transitions cannot be modeled well using claims data.

[20]A few researchers have studied health insurance and/or medical care demand using within-year behavior as an outcome. Keeler and Rolph (1988) and Keeler et al. (1988) use data from the RAND Health Insurance Experiment to examine medical care consumption during treatment episodes in order to study the role of insurance deductibles and stop losses. Aron-Dine et al. (2012) use quasi-experimental data to "investigate whether individuals exhibit forward-looking behavior in their response to the non-linear pricing common in health insurance contracts." Ellis (1986) models demand for mental health services in the first 30, 60, and 90 days of a year as a function of expected end of the year prices, while assuming insurance coverage is determined exogenously. Gilleskie (1998) estimates a structural model of daily medical care consumption and absenteeism during acute illness episodes, also assuming insurance coverage is determined exogenously. Despite the smaller units of behavior, these authors can separately identify adverse selection and/or moral hazard type effects only by using (quasi-)experimental data or simplifying assumptions.

ical care consumption decisions to maximize the value of his expected discounted future utility.[21] The timing of the model can be observed in Figure 1. At the beginning of each year, y, a forward-looking individual observes the set of health insurance alternatives offered by his employer, his general health status, and the presence of any illnesses. Before the start of the first month, $t = 1$, he chooses the health insurance alternative that maximizes his expected discounted future utility. Among other things, this expected utility is a function of anticipated medical care behavior within the year conditional on insurance coverage. In this paper the within-year medical care behavior is modeled explicitly.

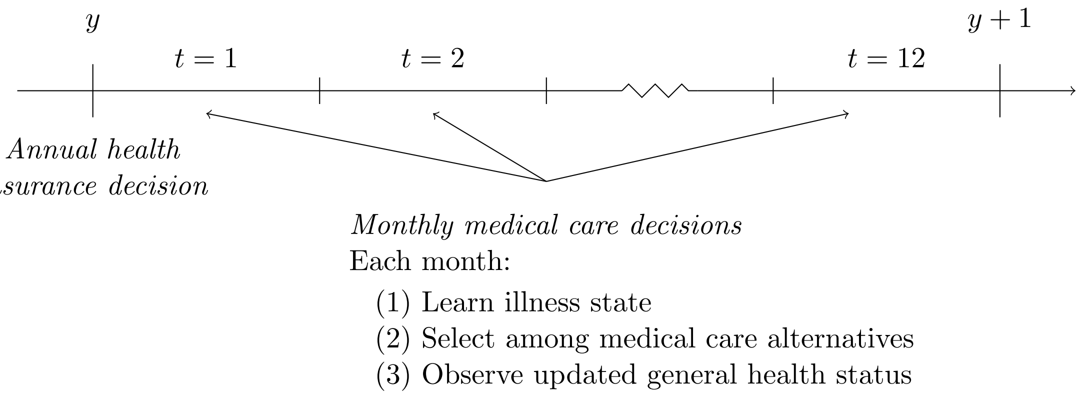
At the beginning of each month, an individual learns his illness state, which evolves stochastically over the course of the year and is influenced by his general health status, illness history, and previous medical care consumption. After learning his current illness state, the individual decides how much (and what types of) medical care to consume. The amount he pays for a unit of medical care depends on the unit price, the cost-sharing characteristics of his health insurance plan, and his accumulated medical care expenditure within the coverage year. Much like the price uncertainty individuals face in the US medical care market, the total price of care is stochastic over time and unknown prior to consumption. After making a medical care decision, the individual's general health status evolves prior to the next month. The remainder of this section explains the model and solution in greater detail.

3.1 Annual and Monthly Decisions

At the beginning of each year, an individual observes the set of health insurance plans available to him from his employer. Each plan is defined by its premium, network type, and a set of cost-sharing characteristics. The cost-sharing features enter an individual's budget constraint throughout the year, determining how much is paid out-of-pocket for medical care. The following

[21] The model features employed individuals who receive an employer-sponsored health insurance offer (ESHI) because health insurance information is only available for these individuals in the data. ESHI is the most popular mechanism by which individuals obtain health insurance in the United States. Of the non-elderly population in 2011: 55.8% held ESHI, 18% were uninsured, 20.5% were insured by state or federal governments, and 5.7% were privately insured (Kaiser Family Foundation). The model focuses on single, childless individuals in order to explicitly capture dynamic health, non-linear out-of-pocket prices, and medical care demand throughout the insurance coverage period. The estimation sample includes men and non-pregnant women.

Figure 1: Timing of the Model



plan characteristics enter the model: out-of-pocket premium, composite annual deductible, doctor's office deductible, hospital deductible, stop loss, hospital co-insurance rate, hospital co-pay level, doctor's office co-insurance rate, doctor's office co-pay level, prescription drug co-insurance, and the extent to which the plan restricts coverage to a network of physicians (HMO, PPO, or FFS).[22] An indicator function, I^j_{iy}, equals one if individual i selects insurance plan j in year y and zero otherwise.[23] Only one plan can be held at a time, so that

$$\sum_{j \in J^i} I^j_{iy} = 1 \quad \forall\, i\, \forall\, y \tag{1}$$

where J^i is the set of exogenously determined employer-sponsored health insurance (ESHI) plans and includes the option to decline all plans.[24]

In each month, an individual learns his illness state (defined below) before making a medical care

[22]A deductible and a stop loss are described in footnote 4. A co-insurance rate is the share of the medical care price that an individual must pay out-of-pocket (the remainder is paid by the insurer). A co-pay level is a fixed dollar amount that an individual must pay out-of-pocket for a unit of medical care (again, the remainder is paid by the insurer). A health maintenance organization (HMO) here refers to an insurance plan that limits its enrollees to receiving medical care from a specified group of providers. A preferred provider organization (PPO) is a plan that defines a preferred network of providers from which care can be purchased less expensively. If an enrollee chooses to seek care outside of this network, coverage is still provided but at a higher out-of-pocket cost. A fee-for-service (FFS) plan covers an enrollee equally at all medical care providers.

[23]For notational simplicity and consistency, I include the subscript i to describe individual level variables only when defining the variable. The subscript i is suppressed thereafter.

[24]Some individuals select a job based (at least partially) on the health insurance offered. However, modeling an individual's decision to accept a particular job, with health insurance options as a job characteristic, requires modeling the employment decision as a function of health insurance characteristics. Thus, this exogeneity assumption has become the norm in the literature.

consumption decision. He chooses the number of doctor visits, v_{it}; hospital days, s_{it};[25] and whether or not to consume prescription drugs, r_{it}.[26] The monthly medical care decision is represented by an indicator function, d_{it}^{vsr}, that equals one if an individual chooses the bundle (v, s, r) and zero otherwise. Bundles are mutually exclusive with a maximum of V doctor visits and S hospital days each month, such that

$$\sum_{v=0}^{V}\sum_{s=0}^{S}\sum_{r=0}^{1} d_{it}^{vsr} = 1 \quad \forall\, i\, \forall\, t. \tag{2}$$

3.2 Health Transitions and Probabilities

Three measures of individual health evolve stochastically over the course of the insurance year. The acute illness state, $A_{it} = \{0, 1\}$, and the chronic illness state, $C_{it} = \{0, 1\}$, are dichotomous. General health status, H_{it}, takes on one of three values: excellent ($H_{it} = 2$), good ($H_{it} = 1$), or poor ($H_{it} = 0$).[27]

I define an acute illness as any medical condition that eventually subsides and, under normal conditions, has no permanent effect on an individual's health or medical care consumption. This characterization describes both short-natured ailments, such as a common cold or influenza, as well as non-permanent but persistent conditions, such as a pneumonia or a broken bone. In estimation, the probability that an individual is in an acute illness state in month t is determined by a logistic function such that

$$P(A_t = 1) = \pi_t^1 = \frac{exp(\alpha_0 + \alpha_1 \mathbf{W_t} + \alpha_2 \mathbf{H_t^A} + \alpha_3 \mathbf{M_{t-1}} + \alpha_4 \mathbf{N_t^A} + \mu_1^k)}{1 + exp(\alpha_0 + \alpha_1 \mathbf{W_t} + \alpha_2 \mathbf{H_t^A} + \alpha_3 \mathbf{M_{t-1}} + \alpha_4 \mathbf{N_t^A} + \mu_1^k)} \tag{3}$$

where $\mathbf{W_t}$ contains demographic factors such as sex, race, income, education, MSA indicator, age and month indicators; $\mathbf{H_t^A}$ is general health status and illness state entering the month

[25]Hospital *days* are chosen rather than the standard (hospital) *nights* because inpatient and outpatient hospital visits are not modeled separately. A visit to the ER and an outpatient procedure each constitute a decision to consume one hospital day. A single overnight visit reflects a decision to consume two hospital days.

[26]According to the Centers for Disease Control and Prevention (CDC) these three types of care account for over 80% of personal medical care expenditure in the United States. For the population being analyzed, the percentage is even higher because individuals are non-elderly and unlikely to consume nursing home care or home healthcare. Other relevant medical care products, such as dental and optical, are unlikely to be covered by standard ESHI plans and are thus excluded from the study.

[27]Death is only observed once in the data because the estimation sample includes ages 19-64, so it is not modeled as a possible health outcome. A *death state* would be a simple addition with alternative data sets.

$(\mathbb{1}_{H_t<2}, \mathbb{1}_{H_t<1}, A_{t-1}, C_{t-1})$; $\mathbf{M_{t-1}}$ is medical care consumption in the prior month $(v_{t-1}, s_{t-1}, r_{t-1})$; $\mathbf{N_t^A}$ contains interactions of the variables in $(\mathbf{W_t}, \mathbf{H_t^A}, \mathbf{M_{t-1}})$; and μ_1^k captures unobserved permanent individual heterogeneity for an individual of type k, where $k = 1, ..., K$.[28] Interactions are used to allow the effect of medical care to vary by illness state entering the month.

I define a chronic illness to be any medical condition that never subsides (e.g., diabetes, asthma, AIDS) or, under normal conditions, has a permanent effect on an individual's health or medical care consumption (e.g., cancer, stroke, hypertension).[29] Given the long-lasting effect of these ailments on health and/or medical care purchasing behavior, the occurrence of a chronic illness is modeled as a permanent, absorbing state. However, medical care can be used to control a chronic illness so that it has a lesser negative impact on an individual's general health status and acute illness probability. I model the probability that an individual is in a chronic illness state in month t as a logistic function such that

$$P(C_t = 1) = \gamma_t^1 = \begin{cases} \dfrac{exp(\delta_0 + \delta_1 \mathbf{W_t} + \delta_2 \mathbf{H_t^C} + \delta_3 \mathbf{M_{t-1}} + \delta_4 \mathbf{N_t^C} + \mu_2^k)}{1 + exp(\delta_0 + \delta_1 \mathbf{W_t} + \delta_2 \mathbf{H_t^C} + \delta_3 \mathbf{M_{t-1}} + \delta_4 \mathbf{N_t^C} + \mu_2^k)} & \text{if } C_{t-1} = 0 \\ 1 & \text{if } C_{t-1} = 1 \end{cases} \tag{4}$$

where $\mathbf{H_t^C} = (\mathbb{1}_{H_t<2}, \mathbb{1}_{H_t<1}, A_{t-1})$.[30]

At the end of each month t an individual's general health status is updated, H_{t+1}, before transitioning to the next month $t + 1$. Motivation for the inclusion of general health status comes from the household production approach of Grossman (1972), who describes both a consumption

[28]See Section 5.1 for a discussion of estimation and interpretation of unobserved permanent individual heterogeneity in this model.

[29]This definition classifies several permanent physiological conditions as chronic illnesses that are not typically categorized as such, because the conditions are likely to impact an individual's future medical care consumption (e.g., amputations, menopause, organ and joint replacement).

[30]The MEPS data classifies illness by ICD-9-CM condition codes, which would allow for a more detailed characterization of illness to be integrated into the model. However, any attempt to more narrowly define illness states would require a significant level of subjectivity and would increase estimation time. For example, I could feasibly model the number of acute and chronic illnesses rather than using the dichotomous classification; however, this extension would require an assumption about whether or not a record of reported diarrhea and reported stomach-ache constitute one illness or two. Similarly, I could define different observed or unobserved classes of acute and chronic illness (Gilleskie, 1998), but again, subjectivity is required in the classification of reported illnesses. Ultimately, empirical implementation of the model as specified reveals how well the three health measures (i.e., monthly transitions in general health status, acute illness state, and chronic illness contraction) and unobserved permanent individual heterogeneity explain medical care consumption behavior. The answer to this question is important given the models of moral hazard that consider only annual medical care consumption and one (or no) measure of health variation.

motive and a production motive for the utilization of medical care. In Grossman's model, an individual consumes medical care to rebuild an ever depreciating *stock* of health. The health stock produces health flows (e.g., healthy days), which directly increase utility and can be used to produce income or other consumption goods. The model presented in this paper takes a similar approach by allowing general health status to enter the utility function and by allowing general health status to be influenced by past health and medical care consumption. I assume general health status has the following ordered structure

$$H^*_{t+1} = \psi_0 + \psi_1 \mathbf{W_t} + \psi_2 \mathbf{H^H_t} + \psi_3 \mathbf{M_t} + \psi_4 \mathbf{N^H_t} + \mu^k_3 + \zeta_{t+1}$$

$$\text{and} \quad H_{t+1} = \begin{cases} 2 & if\ \kappa < H^*_{t+1} \\ 1 & if\ 0 < H^*_{t+1} \leq \kappa \\ 0 & if\ H^*_{t+1} \leq 0 \end{cases} \tag{5}$$

where H^*_{t+1} represents latent general health, $\mathbf{H^H_t} = (\mathbb{1}_{H_t<2}, \mathbb{1}_{H_t<1}, A_t, C_t)$, and κ is a cut-off point to be estimated. Assuming ζ_{t+1} follows a logistic distribution, the (ordered logit) probability of transitioning to each general health level is

$$\begin{aligned} P(H_{t+1} = 2) &= \eta^2_{t+1} = 1 - \Lambda(\kappa - \psi Z_t) \\ P(H_{t+1} = 1) &= \eta^1_{t+1} = \Lambda(\kappa - \psi Z_t) - \Lambda(-\psi Z_t) \\ P(H_{t+1} = 0) &= \eta^0_{t+1} = \Lambda(-\psi Z_t) \end{aligned} \tag{6}$$

where $\psi = (\psi_0, \ldots, \psi_3, \mu^k_3)$, $Z_t = (\mathbf{W_t}, \mathbf{H^H_t}, \mathbf{M_t}, \mathbf{N^H_t})$, and $\Lambda(\cdot)$ is the logistic function. In addition to its theoretical relevance, general health status plays an important role in this model because it gives purpose to medical care consumption when in a chronic illness state, which is important given that chronic illnesses never expire. Through interactions, this specification allows medical care consumption to alter the effect that a chronic illness state has on general health status. For example, according to this model, an individual with diabetes uses insulin to lessen the negative impact of the disease on his general level of health - not to *cure* the disease. The same could be said of open heart surgery, blood-pressure medication, or asthmatic inhalers.

3.3 Utility Function and Budget Constraint

Preferences for a medical care consumption bundle ($v_t = v, s_t = s, r_t = r$) in month t are described by the following contemporaneous utility function[31]

$$U(X_t, R, \mathbf{H_t^U}, d_t^{vsr}, \mu^k, \epsilon_t^{vsr}) = \frac{X_t^{\omega_0 R}}{\omega_0 R} + \omega_1 \mathbf{H_t^U} + \omega_2 \mathbf{M_t^U} + \omega_3 \mathbf{N_t^U} + \mu_{4v}^k + \mu_{5s}^k + \mu_{6r}^k + \epsilon_t^{vsr}$$
$$= \overline{U}(d_t^{vsr}) + \epsilon_t^{vsr} \tag{7}$$

where X_{it} represents consumption of non-medical goods (determined by the budget constraint defined in Equation 8); $R = (1, sex, race, age)$; $\mathbf{H_t^U} = (\mathbb{1}_{H_t<2}, \mathbb{1}_{H_t<1}, A_t, C_t)$; $\mathbf{M_t^U} = (v_t, s_t, r_t, v_t^2, s_t^2)$; $\mathbf{N_t^U}$ contains interactions of the variables in $(\mathbf{H_t^U}, \mathbf{M_t^U}, \mathbf{W_t})$; the μ^k parameters capture unobserved permanent heterogeneity for an individual of type k; and ϵ_{it}^{vsr} is the unobserved utility received from v doctor visits, s hospital days, and consuming prescription drugs ($r = 1$) or not ($r = 0$).[32]

The monthly budget constraint is

$$X_t = Y_t - P_{jt} - O_t(v_t, s_t, r_t, p_t^v, p_t^s, p_t^r, ADE_t, AHE_t, I_y^j) \tag{8}$$

where Y_{it} is monthly income; P_{ijt} is the month t premium paid out-of-pocket for plan j; $O_t(\cdot)$ is the out-of-pocket expenditure on medical care in month t; p_{it}^v, p_{it}^s, and p_{it}^r represent the total price of a doctor visit, a hospital day, and prescription drugs, respectively; and ADE_{it} and AHE_{it} represent accumulated out-of-pocket medical care expenditure for doctor visits and hospital days entering month t, respectively.[33] This structure assumes that an individual consumes all income by the end of each month, as monthly saving decisions are not observed in the data.[34]

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[31] This utility function is representative when X_t is greater than or equal to zero. If medical care expenditure becomes so great that X_t is negative, then the first term $\frac{X_t^{\omega_0 R}}{\omega_0 R}$ is replaced by $\omega_{40} * X_t$ to capture the (dis)utility of negative non-medical good consumption.

[32] I allow the effect of unobserved permanent individual heterogeneity in the utility function to vary by polynomials in consumption. Thus, unobserved preference for doctor visits is captured by $\mu_{4v} = v\mu_4^a + v^2\mu_4^b$; hospital days by $\mu_{5s} = s\mu_5^a + s^2\mu_5^b$; and prescription drugs by μ_{6r}.

[33] Because an individual faces a binary decision on whether or not to consume any prescription drugs, p_{it}^r is a total monthly expenditure on prescription drugs rather than the unit price per prescription.

[34] French and Jones (2011) examine the effects of health insurance and self-insurance (i.e., savings) on retirement

Having specified the contemporaneous utility function, budget constraint, and all transitions between uncertain illness states and general health status, I denote the set of information known by an individual at the time of a medical care consumption decision, or his *state*, as $\Psi_t = (W_t, H_t, A_t, C_t, ADE_t, AHE_t, I_y^j, \mu^k, \epsilon_t^{vsr})$. It remains to describe what the model assumes about an individual's knowledge of medical care prices and out-of-pocket expenditure; then, the optimization problem can be fully expressed.

3.4 Medical Care Prices and Expenditure

Two characteristics of the medical care marketplace make within-year medical care expenditure an important economic construct. First, most individuals do not pay the total price of medical care because of a cost-sharing arrangement with their health insurance provider.[35] Rather, an individual pays a dollar amount out-of-pocket that is determined by the total price of medical care, insurance plan characteristics, and accumulated medical care expenditure during the coverage year. For example: an individual with a \$300 deductible, 10% co-insurance rate, and \$0 of accumulated expenditure who is charged \$100 for a doctor visit pays the full \$100 out-of-pocket. However, if the same individual were to have accumulated \$250 in medical care expenditure prior to the visit, then he would pay only \$55 out-of-pocket for the visit (\$50 pre-deductible + \$5 [$= 0.1 * (\$100 - \$50)$] post-deductible). An individual with health insurance characterized by this cost-sharing structure, a deductible with a co-insurance rate, faces a non-linear budget constraint. The out-of-pocket expenditure function, $O_t(\cdot)$, is constructed so that the budget constraint in Equation 8 contains these non-linearities. Precise calculations of out-of-pocket expenditure and accumulated out-of-pocket expenditure are detailed in the web appendix.

A second characteristic of the medical care market is that individuals are typically uncertain

behavior. The authors explain that omitting savings from an individual's dynamic problem ignores the ability to smooth consumption through savings, which can potentially overstate the value of insurance. In simulation, they find that omitting savings from the model does increase the value of insurance, but (retirement) decision making is unchanged in the no-savings model.

[35] Medical care can be thought of as having two prices, a *list* price and a *transaction* price. The list price is generally printed on a customer's bill and can be thought of as the theoretical market price for care. The transaction price, which is the sum of the insurer's and insured's payments, is typically lower than the list price as insurance companies negotiate for reduced rates from certain medical care providers. Because the list price is rarely paid in practice, the *total price* in this model refers to the total transaction amount for a unit of medical care, which I observe in the data.

of the total price of medical care prior to consumption. The lack of menu prices, uncertainty of diagnosis prior to a visit, and wide price variation in local medical care markets contribute to price uncertainty.[36] Despite the evidence, surprisingly few models of medical care demand allow for this uncertainty. To address this reality, I assume that an individual does not observe total medical care prices prior to making a medical care decision in each month. Rather, an individual knows the conditional distributions from which doctor visit prices, hospital day prices, and prescription drug prices are drawn. An individual makes medical care decisions by integrating over the three conditional price distributions, which are estimated from the data.[37]

The total price distributions are defined as $F^v(p_t^v|\Phi_t;\lambda^v)$, $F^s(p_t^s|\Phi_t;\lambda^s)$, and $F^r(p_t^r|\Phi_t;\lambda^r)$, where $\Phi_t = (W_t, H_t, A_t, C_t, HMO_j, PPO_j, FFS_j, \mu^k)$ is a vector of variables that explain variation in the distributions and $(\lambda^v, \lambda^s, \lambda^r)$ are parameters to be estimated. The variables HMO_j, PPO_j, and FFS_j are indicators of the plan's coverage type. Coverage type is included to capture the negotiation for lower rates by insurance providers who contract with a network of physicians.[38] An indicator of MSA level is included in W_t to capture urban area variation in prices. In addition to differences attributed to supply side variation, these distributions depend on individual observed illness states and general health status. Finally, these medical care price shocks are likely to be correlated with unobserved illness and health shocks. An individual who receives an exceptionally bad illness shock (e.g., cancer) is also likely to experience a price distribution that is shifted upward or has fatter tails. For this reason, the three medical care price shocks are likely to be correlated with one another as well. I allow the permanent unobservables that influence preferences, illness states, and general health outcomes to also influence the price distributions. Currently, the model does not allow for time-varying unobserved heterogeneity.

[36]In May 2013, the Centers for Medicare and Medicaid Services (CMS) released data showing wide variation in medical care prices in local medical care markets. Such variation makes it difficult for an individual to know medical care prices prior to consumption. Recent articles in Time Magazine and The New York Times have also highlighted the issue of price uncertainty in medical care markets.

[37]An equilibrium model of the medical care market could conceivably allow for price determination in solution. Such a model, to be realistic, would have to include as players individuals, providers, hospitals, insurance companies, employers, and the government since interactions between all of these entities determine prices in the market.

[38]The model does not differentiate between in-network and out-of-network medical care consumption. All medical care is assumed to be in-network. Insurance cost-sharing characteristics are specific to in-network consumption.

3.5 The Optimization Problem

An individual's objective is to maximize his expected discounted future utility by selecting the optimal sequence of medical care bundles, d_t^{vsr}, for $t = 1, ..., T$ and insurance plans, I_y^j, for $y = 1, ...Y$ conditional on his state variables in Ψ_t. I describe an individual's dynamic optimization problem in two stages, as insurance decisions are made at the beginning of a year and medical care is chosen repeatedly over the course of a year.

3.5.1 The Optimal Monthly Decision Rule

Let $V_{vsr}^{ach}(\cdot_t)$ be the month t value of expected discounted future utility for medical care decision d_t^{vsr}, illness state $(A_t = a, C_t = c)$, and general health status $(H_t = h)$. Using Bellman's Equation (Bellman, 1957), this value is constructed as the sum of contemporaneous utility and the expected discounted future utility yielded by the alternative. Conditional on unobserved heterogeneity type k (where $\mu^k = \{\mu_1^k, ..., \mu_{14}^k\}$), insurance plan j, and medical care prices $(p_t^v,\, p_t^s,\, p_t^r)$, the alternative-specific value function can be written, for $t < T$

$$\begin{aligned} &V_{vsr}^{ach}(\Psi_t, \epsilon_t^{vsr} | \mu^k, I_y^j, p_t^v, p_t^s, p_t^r) = \overline{U}(d_t^{vsr}) + \epsilon_t^{vsr} \\ &\quad + \beta \sum_{h'=0}^{2} \left[\eta_{t+1}^{h'}(\Psi_t, d_t^{vsr}) \sum_{a'=0}^{1} \pi_{t+1}^{a'}(h', \Psi_t, d_t^{vsr}) \sum_{c'=0}^{1} \gamma_{t+1}^{c'}(h', \Psi_t, d_t^{vsr}) \left[V^{a'c'h'}(\Psi_{t+1} | \mu^k, I_y^j) \right] \right], \end{aligned} \tag{9}$$

and for $t = T$

$$V_{vsr}^{ach}(\Psi_t, \epsilon_t^{vsr} | \mu^k, I_y^j, p_t^v, p_t^s, p_t^r) = \overline{U}(d_t^{vsr}) + \epsilon_t^{vsr} + \beta \sum_{h'=0}^{2} \left[\eta_{t+1}^{h'}(\Psi_t, d_t^{vsr}) \left[Q_{y+1}(\Psi_0, h') \right] \right] \tag{10}$$

where $\overline{U}(d_t^{vsr})$ is the deterministic part of Equation 7, β is the discount factor, and $Q_{y+1}(\Psi_0, h')$ is the value of expected discounted future utility in month $t = 0$ of year $y + 1$. Maximal expected utility, in illness state $(A_{t+1} = a', C_{t+1} = c')$ with general health status $(H_{t+1} = h')$, in month $t+1$ is

$$V^{a'c'h'}(\Psi_{t+1} | \mu^k, I_y^j) = E_t \left[\max_{vsr} V_{vsr}^{a'c'h'}(\Psi_{t+1}, \epsilon_{t+1}^{vsr} | \mu^k, I_y^j) \right] . \tag{11}$$

The expectation operator is subscripted by t because an individual must form this expectation prior to learning month $t+1$ medical care preference shocks, ϵ_{t+1}^{vsr}.

The value function in Equation 9 is written conditional on realized medical care prices. However, it is assumed that an individual does not know the prices of the three types of medical care prior to consumption; rather, he knows the conditional distributions from which these prices are drawn. Solution to the optimization problem requires integration over these price distributions. The value function, unconditional on prices, is

$$V_{vsr}^{ach}(\Psi_t, \epsilon_t^{vsr}|\mu^k, I_y^j) = \int_{\mathbb{R}_+^3} f^*(p_t^v, p_t^s, p_t^r) V_{vsr}^{ach}(\Psi_t, \epsilon_t^{vsr}|\mu^k, I_y^j, p_t^v, p_t^s, p_t^r) dp_t^v dp_t^s dp_t^r \tag{12}$$

where $f^*(p_t^v, p_t^s, p_t^r) = f^v(p_t^v) * f^s(p_t^s) * f^r(p_t^r)$ and $f^v(\cdot)$, $f^s(\cdot)$, and $f^r(\cdot)$ are the conditional density functions from which p_t^v, p_t^s, and p_t^r are drawn.[39]

Conditional on the prior insurance decision and unobserved heterogeneity, a utility maximizing individual selects each medical care consumption bundle with probability

$$P(d_t^{vsr} = 1) = P\left[V_{vsr}^{ach}(\Psi_t, \epsilon_t^{vsr}|\mu^k, I_y^j) \geq V_{v's'r'}^{ach}(\Psi_t, \epsilon_t^{v's'r'}|\mu^k, I_y^j) \quad \forall \quad v's'r'\right] . \tag{13}$$

3.5.2 The Optimal Annual Decision Rule

The problem can be solved backwards to recover the time $t = 0$, year y value function conditional on any chosen health insurance alternative $j \in J_y^i$. That is,

$$V(\Psi_0, H_1 = h|\mu^k, I_y^j) = \sum_{a=0}^{1} \pi_1^a(\Psi_0, H_1) \sum_{c=0}^{1} \gamma_1^c(\Psi_0, H_1) \left[V^{ach}(\Psi_1|\mu^k, I_y^j)\right] . \tag{14}$$

Stated explicitly, Equation 14 represents the discounted value of optimal future behavior calculated at the beginning of year y unconditional on the first month acute and chronic illness state but conditional on general health status entering the year and insurance plan j (i.e., the expected discounted

[39] Conditional on μ^k (unobserved permanent individual heterogeneity) these distributions are independent; however, their dependence on μ^k allows some correlation.

future value of plan j).[40] This value does not completely determine the optimal insurance alternative, as an individual may have preferences for unobserved insurance characteristics.[41] Therefore, I allow further variation through an additive error term such that the expected discounted future value of plan j is

$$Q_y^j(\Psi_0, H_1, \phi_y^j | \mu^k) = V(\Psi_0, H_1 | \mu^k, I_y^j) + \phi_y^j \ . \tag{15}$$

A utility maximizing individual selects each insurance plan with the probability[42]

$$P(I_y^j = 1) = P\left[Q_y^j(\Psi_0, H_1, \phi_y^j | \mu^k) \geq Q_y^{j'}(\Psi_0, H_1, \phi_y^{j'} | \mu^k) \quad \forall\, j'\right] \ . \tag{16}$$

This optimization problem is consistent with our theoretical understanding of insurance benefits. Health insurance is valuable because it provides risk protection, allows for higher non-medical consumption when ill, and yields health benefits if additional medical care is consumed during a coverage year. Further, the model explicitly captures the non-linear relationship between a plan's expected value at the beginning of a year, its cost-sharing characteristics, and an individual's uncertainty about his future health, medical care prices, and medical care demand.

4 Data

4.1 Description of MEPS

My empirical analysis uses data from the 1996-1999 cohorts of the Medical Expenditure Panel Survey (MEPS).[43] MEPS contains detailed health, medical care expenditure, health insurance, and

[40] Notice that general health status in month 1, H_1, is already known at this time because it was learned during the last month of the prior year.

[41] Unobserved characteristics could be defined coverage restrictions, such as a preexisting condition clause or referral requirement to see a specialist, that simply are not modeled or undefined characteristics that are unlikely to alter the value of a plan but influence individual decisions, such as the plan's order on the application file or brand name.

[42] In the optimization problem, an individual has knowledge of Ψ_0 at the time of an insurance decision, where Ψ_0 contains the chronic illness state learned in the last month of the previous insurance year. In the data, it cannot always be determined whether a chronic illness present in first month of the insurance year (which is often the first month of the survey period) began in the first month or a previous month. Therefore, in order to allow an individual to make health insurance decisions with knowledge of existing chronic illnesses, I assume (in estimation) that he learns his first month chronic illness state prior to his health insurance decision in the first year of optimization.

[43] The data are collected and maintained by the Agency for Healthcare Research and Quality (AHRQ). All data used in estimation are publicly available, with the exception of the individual insurance plan information. These restricted files may only be accessed through a Census Bureau Research Data Center (RDC).

demographic information for a nationally representative sample of families and individuals in the United States. New participants are added annually (beginning in 1996 through the present day), drawn randomly from the previous year's National Health Interview Survey sample. Individuals in each cohort are interviewed 5 times over the 2 years that follow January 1st of their cohort year.

The MEPS has two features that make it particularly well suited for the purposes of this research. First, detailed employer level insurance information, that can be linked to the individual file, was collected for the 1996-1999 cohorts. Data collectors used information gathered in the first interview to contact current main employers, from which they obtained premium and cost-sharing characteristics for all plans offered to the employee. This data feature, which is unique in national survey data, enables me to model a health insurance decision from the full set of available alternatives for individuals with participating employers. However, roughly 50% of individuals participating in MEPS are without insurance information in this *link file* due to employee and/or employer refusal to reveal information.[44] Also, while individuals are interviewed over the course of two years, few employers agree to provide health insurance plan information at the beginning of each year. Therefore, analysis concentrates on one health insurance decision and the medical care decisions in the year that follows for each individual. Second, unlike claims data, the MEPS allows participants to report illness episodes even when they choose not to consume medical care. This data feature allows endogenous illness transitions to be modeled.

A number of important assumptions are required to prepare the data for estimation. For example, each illness, which is defined in the data by an ICD-9-CM medical code, must be interpreted as an acute or chronic illness. Also, medical care consumption dates and partially observable illness dates must be used to determine the starting and ending month of illnesses reported five times over the course of 2 years. I also face the challenge that at least one of the 12 insurance cost-sharing features is missing in 47% of the 5284 plans observed in the data, so imputations must be made.

[44] There was one significant change to the collection process that took place after 1996. The 1996 MEPS asked each employer specific questions regarding their participating employee. This method caused many employees to refuse to provide their employers information as employees wished to remain anonymous. The method was also inconvenient for employers because it was much more difficult to provide information about a particular employee than employees in general. (Legalities also made employers weary of providing employee-specific information.) Therefore, in 1997 the collection process was altered such that employers were asked about their general insurance offerings, but not employee specific offerings. AHRQ then used a matching procedure to identify which offered plan was reportedly chosen by employees.

The magnitude of these complications, and others, and the assumptions required to overcome them are discussed at length in the web appendix.

4.2 Determination of the Sample

The sample used in estimation is taken from the nationally representative sample of single and childless individuals included in the 1996-1999 cohorts of the MEPS survey. (See Table 1 for sample size by inclusion criteria.) I focus on employed individuals between the ages of 19 and 64 whose employers sponsor health insurance coverage.[45] I exclude the unemployed and those employed without an insurance offer because only general insurance information was gathered for these individuals (e.g., coverage status, coverage source, etc.). Employed individuals who receive an insurance offer but choose to be uninsured are included in the estimation sample. These omissions are representative of the sample restrictions found in similar work.[46]

Sample inclusion also requires that the ESHI plans that are offered to an individual are observed in the link file described above. The information contained in the link file is necessary to model an individual's insurance decisions. Individuals must also participate in all interviews during the insurance year. The final restriction limits individuals in the sample to one of two types: (1) individuals taking up ESHI, holding it for an entire year, and holding no outside coverage; or (2) individuals remaining completely uninsured all year. I do not model insurance switching during an insurance year and cannot observe privately purchased plan characteristics.

[45] I study individuals over 18 years old to avoid the unique decision-making process of an adolescent with possible access to his parents health insurance plans. I also exclude full time students under the age of 24 because 1996-1999 federal law allowed these individuals to stay on their parent's insurance plan. Individuals under 64 are targeted because they do not yet have access to coverage through Medicare.

[46] Cardon and Hendel (2001) limit their sample to single, childless, employed individuals who are between the ages of 18 and 64. However, these authors include individuals who are not offered health insurance by their employer. Einav et al. (2013), Kowalski (2013), and Bajari et al. (2013) estimate their models using a sample of individuals employed by one firm. None of the papers include uninsured individuals in the analysis. Einav et al. (2013) model the decisions of families. Kowalski (2013) models the behavior of individual employees, but allows individuals to be in a family of three or fewer people. Bajari et al. (2013) limits analysis to those holding single health insurance coverage.

Table 1: Sample Inclusion Criteria

	1996	1997	1998	1999	Total
1996-1999 MEPS Household Component	22601	13683	11137	14178	61599
and single, childless, 19-64 yrs old	4406	2534	2169	2589	11698
and employed in first interview period with offer	1821	923	987	1128	4859
and matches to link file	749	516	159	688	2112
and no missing interviews	693	472	139	636	1940
and stable insurance status	455	290	98	389	1232

The final estimation sample contains 1232 individuals (or 14784 person-month observations). Table 14, which can be found in Appendix A, compares the 4859 individuals remaining at line 3 above (which is a nationally representative sample of single, childless, 19-64 year olds, who are employed and offered health insurance from their employer) and those in the estimation sample. The table reveals few differences between the estimation sample and a nationally representative sample of this demographic. The estimation sample is slightly older, a little wealthier, and is comprised of a larger proportion of females. These differences contribute to higher medical care expenditure in the estimation sample. The estimation sample is also comprised of more federal employees, which is expected, as no federal employees are excluded due to employer non-response.

4.3 Sample Statistics

The following tables summarize the mean and dispersion of key variables used in estimation. Table 2 compares insured and uninsured individuals in the estimation sample.[47] The insured are older, more educated, and wealthier. They are also more likely to be white and female. The insured are more likely to enter the insurance year with a chronic illness, are more likely to get an acute illness at some point during the insurance year, and have more months where some acute illness is experienced. The insured also consume more units and greater values of doctor and prescription

[47] Most variables are self-explanatory. Income is calculated as the sum of post-tax income, sale earnings, and tax refund. General health status is self-reported, taken from the response to the question "In general, compared to other people of your age, would you say that your health is excellent, good, fair, poor, or very poor?" Roughly 6% of the estimation sample reports poor or very poor health, so the lowest three health categories (fair, poor, and very poor) are combined to form the *poor general health status* category seen in the table and used in estimation. Medical care prices are only observed when medical care is consumed. For more detail on medical care prices, medical care consumption, and illness occurrence see the web appendix.

Table 2: Sample Statistics by Insurance Status

	Insured		Uninsured	
	mean	s.d.	mean	s.d.
Demographics (time invariant)				
age	40.04	11.62	34.73	11.44
education (highest grade completed)	13.73	2.43	12.46	2.49
income (in 1996 dollars)	35198.52	22120.24	19011.55	13144.27
male	0.48		0.52	
lives in a MSA	0.82		0.83	
Hispanic	0.11		0.21	
black	0.14		0.19	
federal employee	0.09		0.09	
Health and Illness (time varying)				
probability of excellent health status in any month	0.31		0.32	
probability of good health status in any month	0.36		0.34	
probability of poor health status in any month	0.33		0.34	
entered year with chronic illness	0.39		0.25	
chronic illness by years end	0.50		0.31	
at least one acute illness during sample year	0.81		0.69	
total months with acute illness	4.62	4.52	2.35	3.21
Medical Care Prices (time varying)				
transaction price for a doctor visit	89.19	159.22	112.43	160.52
transaction price for a hospital day	823.31	1357.76	878.72	2127.58
transaction price for a Rx month	75.22	114.94	49.77	54.43
Medical Care Consumption (time varying)				
at least one doctor visit in sample year	0.74		0.50	
total doctor visits in sample year	5.22	9.35	2.67	5.64
at least one hospital day in sample year	0.25		0.17	
total hospital days in sample year	0.75	2.41	0.99	4.51
at least one Rx month in sample year	0.67		0.45	
total Rx months in sample year	4.69	5.00	2.22	3.91
consumed any preventative care	0.20		0.19	
probability of consumption in any month	0.62		0.45	
probability of consumption in well month	0.13		0.05	
annual value of doctor visits	454.39	951.61	289.67	759.21
annual value of hospital days†	660.28	2706.30	1108.39	6320.84
annual value of Rx consumption	352.80	819.20	110.57	272.71
Other				
number of offered plans	4.41	5.99	3.05	4.46
Sample				
individuals	1119		113	
person-month observations	13428		1356	

† One uninsured individual had hospital expenditures totaling $52,032.16. Removing this outlier lowers the mean to $647.93 for the uninsured.

Table 3: Insurance Plan Summary

	Held Plans			Rejected Plans		
	plans	mean	s.d.	plans	mean	s.d.
Premium						
total premium	1119	2057.19	819.09	4165	2207.13	715.25
out-of-pocket premium	1119	343.83	540.31	4165	519.46	610.28
Deductible†						
defined by total expenditure	397	283.59	272.99	772	293.25	348.26
defined by doctor expenditure only	59	191.38	97.04	655	215.72	50.65
defined by hospital expenditure only	28	252.63	218.10	62	150.58	41.24
plan has no deductible	648			2684		
Stop loss						
stop loss	729	1512.82	1077.97	2775	1689.06	1077.63
plan has no stop loss	390			1390		
Hospital‡						
co-insurance rate	417	17.02	9.91	797	15.44	8.01
co-pay level (per stay)	199	258.46	346.70	768	159.41	194.45
co-pay level (per day)	85	52.61	60.25	142	58.70	85.24
free care past the deductible	435			2577		
Doctor						
co-insurance rate	208	18.91	8.69	755	12.43	7.83
co-pay level	858	10.19	4.53	3110	8.41	4.25
free care past the deductible	53			300		
Network Type						
HMO	1119	0.42		4165	0.51	
FFS	1119	0.47		4165	0.44	
PPO	1119	0.11		4165	0.06	

† These categories are not mutually exclusive. Some of the plans that feature a doctor specific deductible also feature a hospital specific deductible.

‡ These categories are not mutually exclusive. Some of the plans are structured so that an individual pays a daily co-pay, plus a percentage (i.e., co-insurance rate) of the remainder of the bill.

drug care.[48] The percentage of the population that consumes at least one hospital day during the year (25% of insured and 17% of uninsured individuals) seems large, but includes emergency room visits as well as outpatient and inpatient visits. To improve estimation time, I limit the maximum number of doctor visits and hospital days in a month (V and S from Equation 2) to 9 and 5, respectively.[49] The insured face lower (total) prices for doctor visits and hospital days and higher prices for prescription drugs. The large variance in prices is due to the broad classification

[48] While the uninsured are less likely to have at least one hospital day, the average number of hospital days for the uninsured is greater than that of the insured. This is likely due to emergency room usage among the uninsured.

[49] Of the 14,784 person-month observations in the data, the number of doctor visits exceeds the maximum of 9 only 33 times and the number of hospital days exceeds the maximum of 5 only 30 times. In these instances, the number of visits/days is set to the maximum and the average price paid for a unit of medical care is adjusted accordingly. For example, if an individual visits the doctor 12 times in a month with an average price of $100 then the data are adjusted so that he visits the doctor 9 times with an average price of $133.

of medical care consumption types. High priced procedures (e.g., outpatient hospital surgery) and low priced procedures (e.g., emergency room visit for a sprained ankle) contribute to the same price distribution. An individual is considered to have *consumed any preventative care* if during the sample period they consume any form of medical care in a month in which they have no acute illness or chronic illness.

Differences between the chosen and rejected plans can be observed in Table 3. The table suggests that individuals have a general preference for lower premium and therefore less generous (in terms of cost-sharing features) plans. Compared to the average rejected plan, held plans are more likely to have a deductible, less likely to have a stop loss, and set higher thresholds when the plan has a deductible or stop loss. Held plans also feature higher co-insurance rates and co-pay levels for both doctor and hospital care, with the exception of hospital per day co-pay.

4.4 Prescription Drugs

Several assumptions are required to fit the prescription drug data available in the MEPS to the within-year decision-making model presented in Section 3. First, the employer questionnaire used to gather insurance information asks whether each plan "covers" outpatient prescriptions (99% of all plans in the sample do), but does not ask the co-insurance or co-pay level, whether there is a separate deductible for prescription drugs, or whether cumulative deductibles and stop losses apply to prescription drugs expenditure. Therefore, I assume that HMO, PPO, and FFS plans have a fixed prescription drug co-insurance rate of 13%, 17%, and 19% respectively. These rates are consistent with the average rates in the 1996 MEPS Abstraction file.[50] I also assume that prescription drug expenditure is completely unrelated to a plan's deductible and stop loss.[51] This assumption is also informed by the 1996 MEPS Abstraction file, which finds that prescription drug expenditure had no relation to a deductible for 77% of held plans and had no relation to the stop loss for 44%.

[50] Co-pays are a much more popular form of cost-sharing for prescription drugs than co-insurance rates (68% vs. 32% in 1996). However, co-pays make the number and timing of refills a relevant factor in analysis, which I would like to abstract from. Further, 80% of all ESHI plans feature multi-tier prescription drug coverage in the form of co-pays by 2000 (Kaiser EHBAS). Thus, correctly implementing co-pays for prescription drug coverage would require both a quantity and quality decision by individuals.

[51] *Unrelated* means that the insurer and insured share the total cost of prescription drugs from the first day of an insurance year to the last, irrespective of accumulated expenditure. Also, out-of-pocket prescription drug expenditure does not contribute to the accumulated expenditure relevant for the cumulative deductible or stop loss.

According to the Kaiser Family Foundation's Employer Health Benefits Annual Survey, by 2000 prescription drug expenditure had no relation to the stop loss in over 75% of ESHI plans.

Second, I assume that an individual decides whether or not to consume any prescription drugs each month, not the number of prescriptions to fill. In addition to making estimation more tractable, this assumption acknowledges the doctors role in the prescription drug decision. Often times multiple drugs are prescribed such that consuming two, as opposed to one, prescription drugs in no way reflects a marginal decision by an individual and is unlikely to further improve wellness. Also, the survey collects the number of refills of each prescription in each interview period, but provides an exact date only the first time a prescription is purchased. Furthermore, while the exact medication name and quantity are provided, there is no record of whether or not an individual actually consumed the medicine. Therefore, I assume that all patients are prescribed the average dosage for a medication.[52] I then use this dosage, along with the date the prescription was first filled, the number of refills, and the quantity (which is usually number and strength of pills) of the drug in the prescription, to construct a starting date and ending date for each drug consumed. I then smooth payments for the drug over the course of the consumption period, because the model does not distinguish between the payment for and consumption of prescription drugs.

5 Empirical Implementation

For each individual surveyed in the 1996-1999 MEPS I observe one health insurance decision (covering one year of behavior) followed by medical care consumption and prices, illness states, and general health status outcomes over the next two years. Therefore, I estimate the structural parameters of the model described in Section 3 using one year of data for each individual. In what follows, I describe the challenges in estimation, discuss identification and unobserved heterogeneity, and construct the estimated likelihood function.

[52] I use "Mosby's Pharmacology in Nursing," to determine the average dosage of each medication found in the data. My imputations were then double checked by a doctor. More details can be learned in the web appendix.

5.1 Approximating the Future Value of a Medical Care Alternative

Solution to the optimization problem requires the calculation of an individual's value function for each medical care bundle in each month. According to Equation 9, the value of bundle (v, s, r) in month t, $V_{vsr}(\Psi_t)$, is a function of the maximal expected utility in the next month, $V(\Psi_{t+1})$, where the future state vector, Ψ_{t+1}, is unknown. Thus, in order to calculate $V_{vsr}(\Psi_t)$ in practice, a value $V(\Psi_{t+1})$ is needed for every potential outcome of Ψ_{t+1} following every potential history of outcomes $(\Psi_0, \ldots, \Psi_t)$. Given the number of months in a year, the number of variables in the state vector, and the fact that several of the state variables are continuous, the number of required future values grows exponentially.

To avoid what Bellman (1957) refers to as the "curse of dimensionality," I use an interpolation technique developed by Keane and Wolpin (1994) to approximate an individual's maximal expected future value in each month. The method works as follows: beginning in the last month of a year, $t = T$, I draw 3500 random outcomes of the state vector, Ψ_T. I then calculate maximal expected future utility for each draw according to Equation 11. By estimating a linear regression of these values on the state variables in Ψ_T, I generate a mapping from any possible state to expected future values. This mapping can be used in month $T - 1$ to approximate the maximal expected future value of month T, because each alternative in month $T-1$ generates a probability distribution over Ψ_T. By repeating this process backwards (hence backwards solution), I can solve the model back to month $t = 0$.

A related challenge in solving any finite horizon dynamic problem is determining the maximal expected future value in the final period; $Q_y(\Psi_0, H_1)$ from Equation 10. I take a popular approach, which is to formulate a closing function to approximate this value. 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 month of the following year, medical care consumed in month T, and a vector of parameters. I estimate these parameters as part of the MLE procedure.

5.2 Identification

I estimate the following sets of parameters (252 parameters in total)

Acute Illness Parameters:	$\Omega^A = \{\alpha_{00}, ..., \alpha_{49}\}$
Chronic Illness Parameters:	$\Omega^C = \{\delta_{00}, ..., \delta_{32}\}$
Health Status Parameters:	$\Omega^H = \{\psi_{00}, ..., \psi_{49}, \kappa\}$
Price Parameters:	$\Omega^P = \{\lambda_{00}^x, ..., \lambda_{19}^x, \sigma^x\}_{x\in\{v,s,r\}}$
Preference Parameters:	$\Omega^U = \{\omega_{00}, ..., \omega_{40}, \beta\}$
DFRE Parameters:	$\Omega^\mu = \left\{\{\mu_1^k, ..., \mu_{14}^k, \theta^k\}_{k=1}^4\right\}$
Closing Function Parameters:	$\Omega^F = \{\gamma_{00}, ..., \gamma_{11}\}$
Initial Condition Parameters:	$\Omega^I = \left\{\tilde{\alpha}_{00}, ..., \tilde{\alpha}_{19}, \tilde{\delta}_{00}, ..., \tilde{\delta}_{15}, \tilde{\kappa}, \tilde{\psi}_{00}, ..., \tilde{\psi}_{16}\right\}$

Parameters are identified by individual decisions, the model's economic constraints, and parametric assumptions. Identification of acute illness, chronic illness, and general health status parameters comes from the logit assumption and covariance between the independent and dependent variables. For example, the effect of medical care on illness probabilities is identified by individuals in the same illness state making different medical care consumption decisions and getting different illness outcomes the following month. The identification of parameters in the conditional price distributions is similar, though different distributional assumptions are made. Initial condition parameters are separately identified from transition parameters by four exclusion restrictions and the logit assumption.[53]

The identification of the preference parameters is less straightforward. The marginal (dis)utility of medical care, ω_2, is identified through variation in the *types* of medical care consumed, holding state variables fixed. Insurance cost-sharing features help identify these parameters by often making the expected out-of-pocket cost of medical care equal across the three types. The effect of general health status and illness state on utility, ω_1, is identified by the optimization framework and through variation in *total* monthly medical care consumption for individuals in different wellness states. For example, the marginal disutility of acute illness is identified by differences in total consumption between individuals who are identical except in their acute illness states. An acute illness yields disutility if an individual with an acute illness consumes more medical care (and therefore takes on the costs of consuming care) than an individual without an acute illness, in an attempt to cure the illness. This example also explains why the disutility of chronic illness is not identified and

[53] Income last year, an indicator for missing last years income, veteran status, and foreign birth status are included in the estimation of initial condition probabilities but not in transition probabilities.

is, therefore, not included as a direct determinant of utility in estimation. Chronic illnesses never subside, meaning the only justification for additional medical care consumption once a chronic illness is obtained is to diminish the marginal negative effect of that chronic illness on the general health status (and acute illness probability). Therefore, disutility from chronic illness is not separately identified from the disutility of poor general health.

Separately identifying moral hazard effects from adverse selection is an important empirical challenge in this research. There is not a single parameter in the model that identifies the effect of moral hazard (instead, simulation techniques are used); however, the curvature parameters in the utility function, ω_0, are especially important when calculating moral hazard effects because health insurance cost-sharing characteristics and medical care prices enter the optimization problem by altering the consumption of non-medical goods. The data used in estimation have two features that assist in the identification of these parameters. First, twelve medical care decisions, often made at different points in the medical care price distribution, are observed for each individual. The covariance between these decisions and the out-of-pocket cost of medical care helps to identify the curvature parameters. However, the out-of-pocket cost of medical care is endogenous because health insurance is chosen by an individual with expectations of future medical care consumption (adverse selection). A second data feature helps to mitigate this problem. Much like the data used by Cardon and Hendel (2001), each individual in the sample selects health insurance from a different set of alternatives. The degree of variation in the alternative sets is widened by the employer's role in determining the out-of-pocket premium paid for a plan. This variation ensures that individuals with similar expectations of future medical care consumption select different health insurance plans and ultimately face different out-of-pocket medical care costs. If insurance alternative sets are determined exogenously, then the variation in alternative sets reduces the endogeneity of out-of-pocket medical care costs.

Modeling the observed health transitions also helps the model separate selection effects from price effects. In general, the key unobservable that contributes to the unexplained correlation between insurance generosity and annual medical care expenditure is an individual's expectation of future health. If an individual expects poor future health outcomes then he purchases generous coverage and (often) has high medical care expenditures. Rather than using parametric assumptions and the optimization framework to capture heterogeneity in the health expectations that lead to adverse selection, I model observed health and illness outcomes over the health insurance year. By modeling these outcomes and solving the problem backwards, an individual's expectations of future health outcomes are modeled explicitly and impact the valuation of each health insurance plan.

5.3 Unobserved Heterogeneity

I capture unobserved permanent individual heterogeneity in the model using a discrete factor random effects method (DFRE). The DFRE approach avoids restrictive distributional assumptions by allowing the distribution of unobserved heterogeneity to be approximated by a discrete step-wise function (Heckman and Singer, 1984; Mroz and Guilkey, 1992). Mroz (1999), and more recently Guilkey and Lance (2013), use Monte Carlo simulation in a two-equation setting to show that when the true error distribution is joint normal, DFRE estimates are comparable to those derived using the correct distribution. However, when the true error distribution is not normal, the DFRE outperforms all other (tested) estimation methods.

In this model, illness and general health outcomes, medical care prices, and medical care decisions are each partially determined by unobservables (i.e., an error term), which can be decomposed into two components. The first component, a non-linear discrete factor μ^k, represents individual-specific persistent unobserved heterogeneity. The second component is the remaining i.i.d. serially-uncorrelated random error. The population is assumed to have K unobserved types, which are drawn from discrete distribution Θ. The estimation technique determines the value of each discrete factor, $\{\mu_1^k, ..., \mu_{14}^k\}$, for K-1 types (K-1 because identification requires that one type has all discrete factors set to zero) and the probability of each type, θ^k; where $\sum_{k=1}^{K} \theta^k = 1$.

In addition to improving the fit of the model, the DFRE method captures unobserved heterogeneity that may induce adverse selection. For example, an individual with an unobserved (to the econometrician) health condition is also more susceptible to acute illness, chronic illness, poor general health status, and greater medical care consumption. The estimation procedure identifies this unobserved heterogeneity type by unexplained correlation between the dependent variables and allows the type to influence his valuation of each health insurance plan.

5.4 Estimation Procedure

I estimate the model's parameters, Ω, using a nested fixed point solution algorithm (Rust, 1987). The inner algorithm solves the dynamic programming problem for a given set of parameters and for each mass point in the unobserved heterogeneity distribution. The outer algorithm uses the resulting probabilities and densities to calculate the likelihood function, $L(\Omega)$, and attempts to improve the likelihood value using a BHHH gradient method (Berndt, Hall, Hall, and Hausman, 1974).

An individual contributes to the likelihood function the product of his observed illness state, general health status, medical care price, medical care choice, and insurance choice probabilities. General health status and illness state probabilities take on closed forms due to the logit assumptions in Section 3. I assume that doctors prices are drawn from a Singh Maddala distribution and that hospital and prescription drug prices are distributed log-normal.[54] Each of these distributions is characterized by both scale and shape parameters; I allow the scale parameter to vary by state variables. I write the probability density functions as $f^v(\cdot)$, $f^s(\cdot)$, and $f^r(\cdot)$.

I assume ϵ_t^{vsr} and ϕ_y^j each follow a Type 1 Extreme Value distribution. This assumption simplifies estimation in two ways. First, it can be shown that when ϵ_t^{vsr} is Type 1 Extreme Value the expectation in Equation 11 is equal to

$$V(\Psi_t|\mu^k, I_y^j) = EC + ln\left(\sum_{v=0}^{V}\sum_{s=0}^{S}\sum_{r=0}^{1} exp\left(\overline{V}_{vsr}(\Psi_t|\mu^k, I_y^j)\right)\right) \qquad \forall t \tag{17}$$

where EC is Euler's Constant. The assumption simplifies solution to the optimization problem, as calculation/simulation of a $(V * S * 2) - 1$ dimensional integral would be required if another popular continuous distribution without a closed form (e.g., normal) were chosen (see Keane and Wolpin, 1994). Second, the additive Type 1 Extreme Value distribution assumptions yield choice

[54]The methodology used to select these distributions is detailed in the web appendix.

probabilities that have the following closed form structures.

$$P(d_t^{vsr} = 1|\Psi_t, \mu^k, I_y^j) = \frac{exp\left(\overline{V}_{vsr}(\Psi_t|\mu^k, I_y^j)\right)}{\sum_{v'=0}^{V}\sum_{s'=0}^{S}\sum_{r'=0}^{1} exp\left(\overline{V}_{v's'r'}(\Psi_t|\mu^k, I_y^j)\right)} \quad \forall t, \forall vsr \tag{18}$$

$$P(I_y^j = 1|\Psi_0, \mu^k) = \frac{exp\left(\overline{Q}_j(\Psi_0, \mu^k)\right)}{\sum_{j'=0}^{J^i} exp\left(\overline{Q}_{j'}(\Psi_0, \mu^k)\right)} \quad \forall y, \forall j \tag{19}$$

The likelihood contribution for individual i in month t conditional on μ^k and observed H_t is

$$\begin{aligned} L_{it}(\Omega|\mu^k, I_y^j, H_t = h) = &\left([\pi_t^0(\cdot|\mu^k)]^{1-A_t}[\pi_t^1(\cdot|\mu^k)]^{A_t}\right)\left([\gamma_t^0(\cdot|\mu^k)]^{1-C_t}[\gamma_t^1(\cdot|\mu^k)]^{C_t}\right)^{1-C_{t-1}} \\ &\prod_{v=0}^{V}\prod_{s=0}^{S}\prod_{r=0}^{1}\Big[f^v(p_t^v|\mu^k)^{[1-d_t^{0sr}]} f^s(p_t^s|\mu^k)^{[1-d_t^{v0r}]} f^r(p_t^r|\mu^k)^{[1-d_t^{vs0}]} \\ &P(d_{it}^{vsr} = 1|\Psi_t, I_y^j, \mu^k)\prod_{h'=0}^{2}\eta_{t+1}^{h'}(\Psi_t, d_t^{vsr}|\mu^k)^{\mathbb{1}_{H_{t+1}=h'}}\Big]^{d_t^{vsr}} . \end{aligned} \tag{20}$$

The first row contains the illness state contribution for month t. The price densities are in the second row. The $[1 - d_t^{0sr}]$ exponent ensures that price of a doctor visit in month t contributes to the likelihood function only if an individual actually visits the doctor, which is the only time that I observe this price (this is true for each type of care). The third row contains both month t choice probabilities and the probabilities of transitioning to a new general health status entering month $t+1$. To control for endogenous initial conditions, $L_{i1}(\Omega|\mu^k, I_y^j, H_t = h)$ appears as above with the first row replaced by

$$\prod_{h=0}^{2}\left(\tilde{\eta}_1^h(\cdot|\mu^k)^{\mathbb{1}_{H_1=h}}\right)\left([\tilde{\pi}_1^0(\cdot, h|\mu^k)]^{1-A_1}[\tilde{\pi}_1^1(\cdot, h|\mu^k)]^{A_1}\right)\left([\tilde{\gamma}_1^0(\cdot, h|\mu^k)]^{1-C_1}[\tilde{\gamma}_1^1(\cdot, h|\mu^k)]^{C_1}\right) . \tag{21}$$

These initial probabilities $(\tilde{\eta}, \tilde{\pi}, \tilde{\gamma})$ are separately estimated from transition probabilities (with exclusion restrictions) and are allowed to vary by modeled unobserved heterogeneity.

I write $L_{it}(\Omega|\mu^k, I_y^j, H_t = h)$ conditional on $(H_t = h)$ because I only observe general health status in months where an interview is conducted.[55] Therefore, I integrate over the general health status

[55] For most individual's, I observe 4 measures of self-reported health. The first report, which is used for the initial condition, is taken from the NHIS report provided in the previous year. The second and third reports are taken

distribution in months where health is missing. The total likelihood contribution for individual i conditional on μ^k is then written

$$L_i(\Omega|\mu^k) = \prod_{j=1}^{J^i} \left[P(I_{iy}^j = 1|\Psi_0, \mu^k) \prod_{t=1}^{T} L_{it}(\Omega|\mu^k, I_y^j) \right]^{I_{iy}^j}. \tag{22}$$

The contribution of individual i unconditional on the unobserved heterogeneity is

$$L_i(\Omega) = \sum_{k=1}^{K} \theta^k L_i(\Omega|\mu^k). \tag{23}$$

6 Results

This section begins with preliminary parameter estimates. I then discuss model fit, the estimated effect of moral hazard, and model predictions under several counterfactual situations.

6.1 Parameter Estimates

Table 4 reports estimated preference parameters. A constant relative risk aversion (CRRA) parameter, RA, can be calculated for each individual using $(\omega_{00}, \omega_{01}, \omega_{02}, \omega_{03})$.[56] Non-whites and males are found to be significantly less risk averse than whites and females. Risk aversion is increasing in age.[57] A 40 year-old white male has $RA = 0.866$, whereas a 40 year-old white female has $RA = 0.879$. At the sample mean, $RA = 0.925$. These estimates are between the Blau and Gilleskie (2008) estimate of 0.96 and the Imai and Keane (2004) and Sauer (2012) estimate of 0.74; none of which allow for heterogeneity in risk preferences by demographic group. Parameters $(\omega_{10}, \ldots, \omega_{12}, \omega_{30}, \ldots, \omega_{32})$ capture disutility from poor health and acute illness. Note that an in-

from MEPS interviews conducted during the health insurance year. The fourth report is take from the third MEPS interview, which occurs during the insurance year for some, but occurs after the end of the insurance year for others. I use the third interview self-reported health level for the the last month general health outcome even if the interview occurs past the end of the health insurance year.

[56] The CRRA risk aversion parameter is calculated as $RA = [1 - \omega_{00} - \omega_{01} * age - \omega_{02} * nonwhite - \omega_{03} * male]$. Age is scaled in estimation so that the youngest individual included (19) has an age of 0. A 40 year-old, then, has an age of 21.

[57] There is a large literature on the relationship between risk aversion and demographics. Croson and Gneezy (2009) summarize the literature on gender and risk and cite many papers that find women to be more risk averse. Eckel (2008) also find that women are more risk averse than men, but find no significant race effect and mixed age effects. Rosen et al. (2003) find gender and race effects that are similar to those that I find, but do not study age.

dividual in good (but not excellent) health receives a contribution of ω_{10} to his utility function, while an individual in poor health receives a contribution of $\omega_{10} + \omega_{11}$. The direct utility effect of medical care consumption is captured by $(\omega_{20}, \ldots, \omega_{24}, \omega_{33}, \ldots, \omega_{38})$.[58] Interpreting the linear and quadratic consumption terms is not useful without also considering the discrete factor terms discussed in the next paragraph. However, these parameters do reveal that men have significantly lower preferences for doctor visits and prescription drugs than women. Further, preferences for doctor visits are decreasing in age while preferences for prescription drugs are increasing in age. The final parameter of the utility function reflects the disutility of each dollar of negative consumption (i.e., outspending monthly income, requiring an individual to use savings or to borrow) and is not currently estimated.

The parameters in Table 5 describe the discrete step-wise function used to approximate the joint distribution of unobservables in the model. The technique uses the estimation procedure to group the population of individuals by unobservables and estimate the relative effect these groups have on the model's probabilities, along with the probability of being in a particular group.[59] For identification, one group's mass points and probability parameter must be normalized to zero (though not necessarily the same group). I fix both for group 1. Estimation reveals that 7.5% of the population is in group 1. The preference parameters in Table 4 fully describe preferences for this group. One oddity of this group is that its females derive utility directly from prescription drug consumption (ω_{24}). The other three groups are similar in health and in medical care preferences (μ_1-μ_6 in Table 5). In comparison to group 1, these individuals are less likely to get an acute illness, more likely to get a chronic illness, and are in a better general health status. They also receive greater disutility from all 3 medical care types.

It is well known in the health economics literature that estimating the productive effects of med-

[58] These parameters can be interpreted as the *net* direct effect of medical care consumption on utility. The physical, psychological, and time cost of medical care consumption may have negative effects on these parameters. However, some individuals may enjoy consuming medical care, independent of its productive health effects, which has a positive effect on these parameters.

[59] The number of points of support (or groups) is chosen by the econometrician. It is suggested by Mroz (1999) that this number should be chosen using an "upwards-testing approach based on the increase in the quasi-likelihood function value when one adds an additional point of support." This technique is cost prohibitive in this work because additional mass points increase estimation time substantially. Instead, I use an upwards-testing approach that requires a significant improvement in the likelihood function *and* an improvement in model fit to add additional points of support. I arrive at 4 mass points in the current model.

Table 4: Preference Parameter Estimates

	Parameter	Estimate	SE
Utility Function			
RA constant	ω_{00}	0.1785	0.0073
RA age	ω_{01}	-0.0030	0.0003
RA non-white (black or Hispanic)	ω_{02}	0.0324	0.0055
RA male	ω_{03}	0.0126	0.0059
less than excellent health	ω_{10}	-18.5305	2.9335
less than good health	ω_{11}	-13.8780	1.8515
acute illness	ω_{12}	-17.2095	3.3050
doctor visits	ω_{20}	-0.2258	0.0814
doctor visits^2	ω_{21}	0.0355	0.0053
hospital days	ω_{22}	-2.8720	0.2164
hospital days^2	ω_{23}	0.4089	0.0422
any Rx consumption	ω_{24}	1.8402	0.3495
less than excellent health*age	ω_{30}	0.0280	0.0223
less than good health*age	ω_{31}	-0.0031	0.0264
acute illness*age	ω_{32}	-0.0139	0.0170
doctor visits*age	ω_{33}	-0.0080	0.0009
doctor visits*male	ω_{34}	-0.1888	0.0215
hospital days*age	ω_{35}	0.0014	0.0030
hospital days*male	ω_{36}	0.0811	0.0586
any Rx consumption*age	ω_{37}	0.0411	0.0047
any Rx consumption*male	ω_{38}	-1.5221	0.0869
negative consumption†	ω_{40}	0.0010	
Other			
discount factor†	β	0.996	
log-likelihood value‡	$L(\Omega)$	-78920.570	

† Not currently estimated. Note that β is set to 0.996, instead of the traditional 0.95, because this is a monthly model. $0.996^{12} \approx 0.95$
‡ The log-likelihood value with only one unobserved mass point is -82869.49.

ical care (on health and/or illness) is challenging. The unconditional correlation between medical consumption and wellness is usually negative because an individual consumes more medical care when sick. The negative correlation likely reflects bias associated with selection into consumption and omitted health or medical care heterogeneity. In this research, I address the first issue by modeling medical care consumption (i.e., the heath input) and allowing for common unobserved individual heterogeneity that affects both medical care decisions and health outcomes. I address the second issue by simultaneously controlling for 3 measures of health (i.e., acute illness, chronic illness, and general health status) and by allowing the productivity of each type of medical care to vary by illness state. Table 6 reports acute and chronic illness probability parameter estimates and Table 7 contains general health status probability parameter estimates. For each health outcome,

Table 5: Permanent Unobserved Heterogeneity Parameter Estimates

	Param.	Type 1	Type 2 est.	Type 2 s.e.	Type 3 est.	Type 3 s.e.	Type 4 est.	Type 4 s.e.
Mass Point Location								
acute illness probability	μ_1	0.0	-0.955	0.087	-0.282	0.085	-0.410	0.090
chronic illness probability	μ_2	0.0	4.782	1.059	4.959	1.055	4.625	1.052
health status probability	μ_3	0.0	0.141	0.055	0.168	0.055	0.050	0.053
doctor visit preference (linear)	μ_4^a	0.0	-0.859	0.065	-0.400	0.057	-0.333	0.055
doctor visit preference (squared)	μ_4^b	0.0	0.064	0.009	0.016	0.009	-0.005	0.008
hospital day preference (linear)	μ_5^a	0.0	-1.076	0.191	-0.041	0.087	-1.371	0.217
hospital day preference (squared)	μ_5^b	0.0	0.296	0.056	0.093	0.037	0.313	0.065
any Rx preference	μ_6	0.0	-6.026	0.269	-1.569	0.257	-1.117	0.262
doctor visit price distribution	μ_7	0.0	0.034	0.028	-0.025	0.032	-0.187	0.031
hospital day price distribution	μ_8	0.0	0.021	0.047	-0.112	0.122	0.078	0.150
monthly Rx price distribution	μ_9	0.0	-1.658	0.026	-2.104	0.020	-1.019	0.021
initial acute illness probability	μ_{10}	0.0	-1.077	0.336	0.117	0.366	0.091	0.372
initial chronic illness probability	μ_{11}	0.0	-1.624	0.448	0.175	0.466	0.397	0.495
initial health status probability	μ_{12}	0.0	0.905	0.298	0.761	0.322	0.661	0.329
Type Probabilities†								
parameter estimate	θ	0.0	2.038	0.143	0.803	0.159	0.863	0.159
type probability		7.5	57.6		17.0		17.9	

† Probabilities are derived from estimation of parameter θ^k such that $Pr(\mu^k) = \frac{exp(\theta^k)}{\sum_{k'=1}^{4} exp(\theta^{k'})}$.

parameter estimates tell a consistent story of wellness persistence (i.e., if an individual has ailment A in month t then he is more likely to have ailment A in month $t+1$) and cross-wellness effects (i.e., if an individual has ailment A in month t then he is more likely to have ailment B in month $t+1$). The effectiveness of medical care varies by care type and health measure. All medical care types are productive in preventing and curing an acute illness. Only prescription drugs (δ_{32}) are productive in preventing chronic illness. In fact, doctor visits and hospital days are found to increase the likelihood of chronic illness, though the effect is small.[60] Medical care does little to improve an individual's general health status. Neither doctor visits ($\psi_{30}, \psi_{40}, \psi_{43}$) nor hospital days ($\psi_{31}, \psi_{41}, \psi_{44}$) positively impact general health status transitions. However, acute and chronic illness does impact transitions between the healths status outcomes. Prescription drugs maintain or improve general health status when an individual has a chronic and acute illness ($\psi_{32}, \psi_{42}, \psi_{45}$).[61]

[60]Medical care consumption types are not interacted with illness states in the chronic illness probability because there is not enough variation in the data to identify the parameters. Keep in mind that 39% of the population enters the insurance year with a chronic illness, so they provide no contribution to the monthly probability of chronic illness contraction. By years end, 50% of the total population has a chronic illness, meaning that of the (roughly) 8,100 chronic illness probability contributions to the likelihood function, only 135 reflect chronic illness contraction.

[61]While seemingly counter-intuitive, it is not too surprising that medical care consumption has few positive ef-

Table 6: Illness Probability Parameter Estimates

	Parameter	Estimate	SE
Acute Illness†			
constant	α_{00}	-1.6066	0.1690
male	α_{10}	-0.4522	0.0399
non-white (black or Hispanic)	α_{11}	-0.1844	0.0413
education (highest grade completed)	α_{12}	0.0154	0.0073
age	α_{13}	-0.0046	0.0041
lives in a MSA	α_{14}	-0.0015	0.0169
income (in 1996 dollars)	α_{15}	0.0028	0.0011
acute illness	α_{20}	2.7578	0.0824
chronic illness	α_{21}	0.2383	0.0802
less than excellent health	α_{22}	-0.0050	0.0472
less than good health	α_{23}	0.4982	0.1235
doctor visits	α_{30}	-0.1120	0.0210
hospital days	α_{31}	-0.1346	0.0284
Rx consumption	α_{32}	-0.2751	0.0476
acute illness*doctor visits	α_{40}	0.0444	0.0151
acute illness*hospital days	α_{41}	0.0557	0.0240
acute illness*Rx consumption	α_{42}	0.1069	0.0448
chronic illness*doctor visits	α_{43}	0.0637	0.0141
chronic illness*hospital days	α_{44}	0.0867	0.0241
chronic illness*Rx consumption	α_{45}	0.0108	0.0099
acute illness*age	α_{46}	0.0238	0.0034
chronic illness*age	α_{47}	0.0034	0.0031
less than excellent health*age	α_{48}	0.0021	0.0044
less than good health*age	α_{49}	-0.0082	0.0049
Chronic Illness			
constant	δ_{00}	-9.2185	1.0961
male	δ_{10}	-0.0243	0.0203
non-white (black or Hispanic)	δ_{11}	-0.0746	0.0250
education (highest grade completed)	δ_{12}	0.0097	0.0052
age	δ_{13}	-0.0130	0.0019
lives in a MSA	δ_{14}	0.2156	0.0431
income (in 1996 dollars)	δ_{15}	0.0011	0.0006
acute illness	δ_{20}	0.1573	0.0331
less than excellent health	δ_{21}	0.6176	0.1283
less than good health	δ_{22}	0.5753	0.1241
doctor visits	δ_{30}	0.2018	0.0140
hospital days	δ_{31}	0.1074	0.0260
Rx consumption	δ_{32}	-1.9013	0.1305

† Month indicators are included in regression but are not reported here.

Table 7: General Health Status Probability Parameter Estimates

	Parameter	Estimate	SE
General Health Status			
constant	ψ_{00}	4.3994	0.1663
male	ψ_{10}	-0.0864	0.0333
non-white (black or Hispanic)	ψ_{11}	0.0097	0.0329
education (highest grade completed)	ψ_{12}	0.0165	0.0061
age	ψ_{13}	-0.0066	0.0039
lives in a MSA	ψ_{14}	-0.0004	0.0042
income (in 1996 dollars)	ψ_{15}	0.0049	0.0011
acute illness	ψ_{20}	-0.1424	0.0573
chronic illness	ψ_{21}	-0.4984	0.0656
less than excellent health	ψ_{22}	-2.8126	0.1580
less than good health	ψ_{23}	-2.9158	0.1527
doctor visits	ψ_{30}	-0.1231	0.0137
hospital days	ψ_{31}	-0.1989	0.0228
Rx consumption	ψ_{32}	-0.4861	0.0526
acute illness*doctor visits	ψ_{40}	0.0711	0.0088
acute illness*hospital days	ψ_{41}	0.0896	0.0147
acute illness*Rx consumption	ψ_{42}	0.1282	0.0238
chronic illness*doctor visits	ψ_{43}	0.0330	0.0064
chronic illness*hospital days	ψ_{44}	0.0582	0.0151
chronic illness*Rx consumption	ψ_{45}	0.4655	0.0492
acute illness*age	ψ_{46}	-0.0005	0.0024
chronic illness*age	ψ_{47}	-0.0005	0.0024
less than excellent health*age	ψ_{48}	0.0103	0.0055
less than good health*age	ψ_{49}	-0.0159	0.0051
cut-point	κ	3.4409	0.0690

Month indicators are included in estimation but are not reported here.

Price, initial condition, and closing function parameters can be found in Tables 15, 16, and 17, which are located in Appendix A.

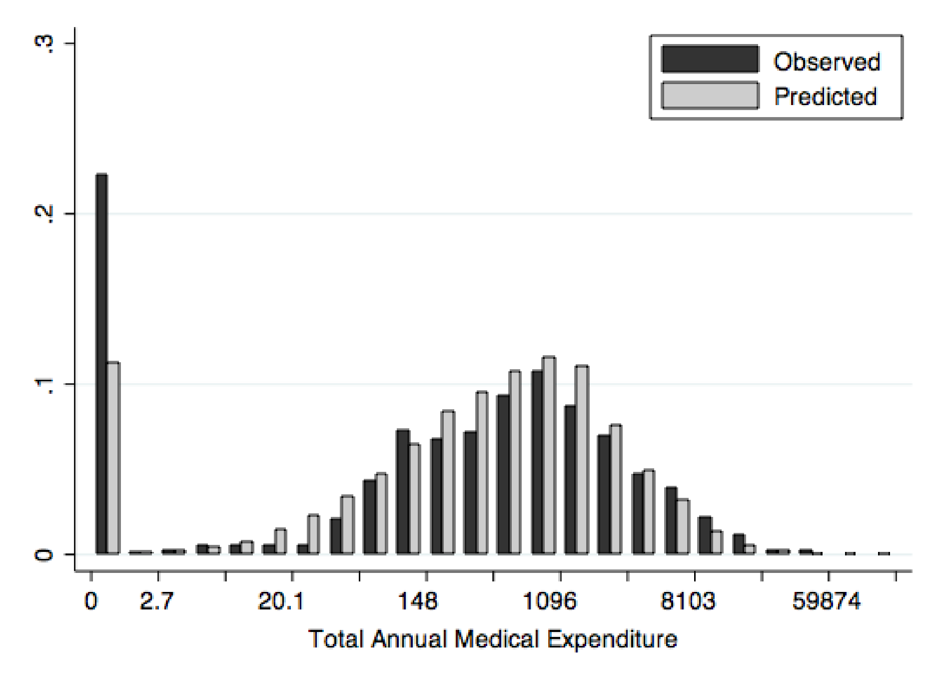
6.2 Model Fit

I use simulation techniques to assess the fit of the model. Using observed initial conditions and insurance offer sets, I simulate annual insurance and monthly medical care decisions, monthly illness state and general health status transitions, and monthly medical care prices for each of the 1232 observed individuals. Using random draws from the appropriate error distributions, I replicate the simulation 100 times. I compare the average across simulated replications with their observed

fects on general health status given that the measure is self-reported. Medical care consumption could serve as a signal/reminder to an individual that he is not in perfect health, making a negative report more likely.

counterparts. Standard errors have not yet been calculated for model fit comparisons.

Figure 2: Annual Medical Care Expenditure



This figure compares observed and simulated annual expenditure distributions. The horizontal axis is log-scaled, so that markers are spaced $exp(1.0)$ apart.

A good indicator of model fit is total annual expenditure, as it requires proper fit of all three consumption and price distributions. Figure 2 shows both observed and simulated annual expenditure distributions. The figure reveals an underprediction of zero medical care expenditure (11% of the simulated sample vs. 22% of the observed data). What is not immediately evident from the figure, but is shown in Table 8, is that the observed distribution also has a higher mean and standard deviation than the simulated distribution. Matching the observed annual expenditure distribution is a difficult endeavor even in annual expenditure models. The research cited earlier often struggles to explain the same unique features of the observed expenditure distribution seen here; namely, the large mass at zero and the long right tail. In this paper, annual medical care expenditure is an outcome that is determined by unit consumption decisions and prices. Table 8 shows that the simulated means and standard deviations of all three price distributions are lower than those of the observed distributions. Most importantly, the standard deviation of the simulated doctor visit price distribution is much lower than the standard deviation of the observed distribution. Experimentation has shown that when the price parameters are adjusted so that the simulated means and standard deviations more closely match the observed, the mean and standard deviation of the simulated expenditure distribution improves substantially. This improvement comes at little or no cost to the fit of other simulated variables. Thus, the fit of the price and expenditure distributions may benefit from an alternative distributional assumptions for prices.

Table 8: Observed and Simulated Outcomes

	Observed			Simulated		
	mean	median	s.d.	mean	median	s.d.
Total Annual Expenditure	1470.09	347.58	3654.74	1243.80	425.25	2761.98
Medical Care Prices†						
doctor visit price	90.26	55.00	159.30	89.46	63.54	87.42
hospital day price	828.10	329.60	1436.26	827.42	342.88	1364.75
prescription drug price	74.06	41.62	112.99	67.31	37.08	90.71
Medical Care Consumption						
annual doctor visits	4.89	2.00	8.69	4.83	2.00	6.26
annual hospital days	0.65	0.00	2.00	0.60	0.00	1.40
months with Rx cons.	4.46	2.00	4.95	4.17	2.00	4.43
% consuming (any month)	43.59			44.17		
% consuming when $A_{it} = 1$	71.70			70.79		
% consuming when $C_{it} = 1$	72.89			69.17		
% consuming when $A_{it} = C_{it} = 0$	9.25			15.07		
Monthly Health						
% with acute illness	36.41			34.79		
% with chronic illness	44.03			43.75		
% in excellent health	32.55			31.03		
% in good health	35.82			38.89		
% in poor health	31.63			30.08		
Held Insurance Types						
% No Insurance	9.16			16.52		
% HMO	37.96			33.55		
% PPO	10.14			9.89		
% FFS	42.74			40.03		

† Prices are only observed when an individual consumes medical care; thus, the simulated mean and standard deviation are calculated only from individuals consuming care in simulation.

Simulated annual medical care consumption and monthly consumption by illness state appear to match the observed data well in Table 8. However, the full consumption distributions displayed in Table 9 mirror a problem with the expenditure distribution; the model is currently unable to generate enough zero-consumers. The largest difference is found for doctor visits. Again, manual manipulation of model parameters shows that if these consumption distributions can shift some mid-range consumers to zero consumption, then the expenditure distribution improves.[62]

Table 9: Observed and Simulated Annual Consumption

	Doctor visits		Hospital days		Prescriptions	
	obs.	sim.	obs.	sim.	obs.	sim.
0	28.22	18.94	75.83	72.25	35.44	30.43
1	16.06	17.76	12.08	16.40	13.06	14.36
2	12.73	12.68	4.87	4.46	5.92	8.11
3-5	18.41	21.22	4.79	5.07	8.14	13.09
6-9	10.46	13.88	1.46	1.52	7.79	12.31
10+	14.12	15.52	0.97	0.30	27.66	21.69

The table reports annual consumption levels for the observed and simulated samples. The values are the proportion of the samples consuming at each level. For example, the top left entry states that 28.22% of the observed sample visited a doctor's office zero times during the insurance year. The prescription drug levels are measured in consumption months.

Table 8 also reveals that simulated monthly health status and illness state probabilities match the observed data well. With regard to the fit of health insurance type, the current parameter estimates predict that too many individuals choose to be uninsured. The overprediction is a result of the expenditure distributions' thin right tail. When the variances of medical care prices are manually increased to match the data, not only does the mean and variance of the expenditure distribution increase but the likelihood of being insured does as well.

6.3 Moral Hazard

Empirical studies of moral hazard often quantify the effect of insurance possession on medical care consumption and, at times, measure the welfare implications of this additional consumption. In this paper, I do the former and discuss the latter in the web appendix. A well known measure of the relationship between a health insurance and medical care demand is the single price/co-insurance elasticity of medical care demand, which was made popular by RAND Health Insurance Experiment (HIE) researchers. In more recent work, researchers have calculated the proportion of total annual expenditure (when insured) that is caused by insurance possession (Bajari et al.,

[62]The DFRE method being used does improve the fit of all 3 consumption distributions in the appropriate directions (namely, the model that allows for four unobserved types generates significantly more zero-consumers than the model with only one unobserved type). However, adding additional mass points does not further improve the fit of these distributions. The model is currently being reestimated with a more flexible medical care preference structure to allow for more zero-consumers.

2013) as a measure of moral hazard effects. My preferred measure, and the measure that I focus on in this research, is the average increase in total annual expenditure due to insurance coverage (Einav et al., 2013).

To be more precise, I calculate the percentage increase in mean total annual medical care expenditure in the population when individuals are moved from an uninsured state into their preferred health insurance plan. I calculate this statistic in two stages. In the first stage, I use the model to forward simulate behavior assuming that all individuals are without insurance. In the second stage, I simulate the model while forcing all individuals to select a health insurance plan from the alternative set offered by their employer. Mean predicted expenditure without coverage is \$668. Row 1 of Table 10 reports the predicted increase in total annual medical care expenditure when individuals move from no insurance to their preferred plan. Mean expenditure increases by \$615, or by 92%; however, these moral hazard effects vary widely across the population and are driven by those with very large increases in expenditure. If the top 1% of additional spenders (i.e., those with spending increases in excess of \$10,515) are removed, then the mean expenditure increases 65% in response to insurance acquisition. Furthermore, 44% of the sample does not increase their spending at all in response to coverage. In Row 2, I report the estimated effect of moral hazard on expenditure when individuals are moved from no coverage to full coverage, which allows for comparisons across papers. The out-of-pocket insurance premium is assumed to be zero with full coverage.

Table 10: Predicted Effect of Moral Hazard on Medical Care Expenditure

	Mean	25th	50th	75th	90th	95th
Increase in expenditure when moved from						
no coverage to preferred coverage	615	0	22	300	1,445	3,122
no coverage to full coverage	741	0	84	583	2,027	3,806

As stated above, there are many different measures moral hazard effects reported in the literature. By simulating behavior under various insurance conditions, I am able to calculate several of these measures using my model and data. These comparisons are reported in Table 11. As presented in Row 1, Manning et al. (1987) use the experimental RAND HIE data and "two- and four- part" models to estimate a co-insurance (arc) elasticity of medical care demand of 0.17 for the 0-25% co-insurance range and 0.22 for the 25-95% co-insurance range. To calculate comparable measures, I simulate the within-year decision-making model under three cost-sharing arrangements. All three arrangements feature no deductible, no stop loss, and no premium; differing only by a universal co-insurance rate, which is set to 0%, 25%, or 95%.[63] I estimate a co-insurance elasticity of medical care demand of 0.18 for the 0-25% co-insurance range and 0.28 for the 25-95% co-insurance range. The remaining three comparisons are straightforward. The measures used by Keeler and Rolph (1988) and Einav et al. (2013) compare expenditure under full insurance and no insurance. The measure used by Bajari et al. (2013) compares expenditure under no insurance and observed/preferred insurance status.[64]

This exercise highlights an important feature of the within-year decision-making model. In principle, the flexibility of the model allows one to calculate other measures of moral hazard effects that are observed in the literature so that comparisons can be drawn. However, despite my efforts, the various moral hazard measures reported in Table 11 are not truly comparable. Each of these studies uses a different population of individuals in their empirical analysis. These populations differ in observed features, likely differ in unobserved features, and select health insurance from different sets of alternatives; all of which are likely to impact the estimated effect of moral hazard on medical care consumption.[65]

[63]The RAND HIE plans had no premium and those used for price elasticity estimation had no deductible. The plans did feature a $1000 stop loss, but efforts are made by the researchers to avoid the distortions in price elasticity estimates caused by this dynamic incentive for reasons explained in Keeler et al. (1977). Specifically, Manning et al. (1987) "examine demand for episodes of treatment by individuals who are more than $400 from their (stop loss) limit. This strategy gives an approximation of the true price effect if such people treat the true probability of exceeding their limit as nearly zero." Rather than recreating their approximation technique, I eliminate the stop loss in simulation.

[64]Kowalski (2013) also estimates the average increase in expenditure when moved from no insurance and full coverage. She finds an increase of only $16 (in 2003 dollars), meaning a comparable moral hazard estimate to Einav et al. (2013) would be less than 1%. Also, note that Bajari et al. (2013) do not allow for income effects in their estimate, by adjusting the budget constraint in the no-insurance case so that the observed consumption bundle is guaranteed to be affordable. Their estimate would increase without this adjustment.

[65]The RAND HIE data used by Manning et al. (1987) and Keeler and Rolph (1988) include both children and married individuals, while my data do not. Einav et al. (2013) and Bajari et al. (2013) use claims data from a single employer, though not the same employer. In general, employer data feature a more homogenous population and insurance plans are selected from a limited set of health insurance alternatives, which are subsidized by the employer. Analysis is also limited to insured individuals, as claims data are not collected for those declining coverage. Bajari et al. (2013) include all employees selecting single coverage, while Einav et al. (2013) include all employees. Also, individuals in each of these studies face vastly different healthcare environments, as my data were collected from 1996-1999, the RAND HIE data used by Manning et al. (1987) and Keeler and Rolph (1988) were collected from 1974-1980, and the claims data used by Einav et al. (2013) and Bajari et al. (2013) were collected from 2003-2006 and 2002-2004, respectively.

Table 11: Other Measures of the Effects of Moral Hazard

	Measure	Reported Estimate	Within-Year Model Estimate
Manning et al. (1987)[a]	Co-insurance arc elasticity of medical care demand 0%→25%, 25%→95%[b]	0.17, 0.22	0.18, 0.28
Keeler and Rolph (1988)	Proportion of full insurance expenditure not explained by moral hazard[c]	55%	49%
Einav et al. (2013)	Percentage increase in mean annual expenditure, no insurance to full coverage[d]	30%	111%
Bajari et al. (2013)	Proportion of preferred insurance expenditure explained by moral hazard[e]	45%	48%

a These results are also reported in Keeler and Rolph (1988).
b The arc elasticity is calculated as $E_{arc} = ((q_2 - q_1)/(p_2 - p_1)) \times ((p_2 + p_1)/2)/((q_2 + q_1)/2)$, where q is mean annual medical care expenditure and p is the co-insurance rate. Manning et al. (1987) make this calculation for each type of care and then weight elasticities for various types of care by share of spending.
c q_{2i}/q_{1i} is calculated for each individual, where q_{2i} is total annual medical care expenditure with a 95% co-insurance rate (near no insurance) and q_{1i} is total annual medical care expenditure with full insurance for individual i. The population mean is reported above.
d $(q_2 - q_1)/q_1$ is calculated, where q_2 is mean total annual medical care expenditure for the population under full coverage and q_1 is mean total annual medical care expenditure for the population under no coverage.
e $(q_{2i} - q_{1i})/q_{2i}$ is calculated for each individual, where q_{2i} is total annual medical care expenditure with preferred/chosen coverage and q_{1i} is total annual medical care expenditure with no coverage for individual i. The population mean is reported above.

Thus, two conclusions can be drawn. First, the comparisons made in Table 11 serve to provide some external validity for my findings. The table suggests that the within-year model predicts a level of price sensitivity that is near what has been found in the literature, but due to both observed and unobserved differences in estimation samples, these estimates are not directly comparable with those found in the literature. Second, an important objective of this research project is to determine whether or not a model of within-year medical care decision making produces moral hazard effects that are different from an annual expenditure model. One way to answer this question is to compare my estimates to the estimates of (Bajari et al., 2013) or (Einav et al., 2013), who each estimate structural annual expenditure models. However, again due to differences in estimation samples, this approach would be naive.

In what follows, I perform a series of counterfactual simulations to study how different assumptions imposed on a within-year decision-making model lead to different moral hazard effects. By using the same model and data across simulations, I can isolate the impact that specific assumptions have on estimated moral hazard effects, which is not possible when comparing results across papers. The most important counterfactual imposes on the within-year decision-making model a set of assumptions that are consistent with the assumptions made implicitly in most annual expenditure models.

6.3.1 Moral Hazard and Modeling Assumptions

The assumptions imposed on a behavioral model are likely to impact the estimated effects of moral hazard. For example, if medical care consumed over the course of the insurance year is allowed to improve an individual's health, then simulating behavior under no coverage should produce the following: an immediate reduction in medical care consumption due to higher out-of-pocket costs (price effect), followed by an increase in the occurrence of illness and poor health outcomes, followed by an increase in medical care consumption (health effect), as he attempts to cure the illness and improve his health status. A model that does not allow medical care to improve future illness and health outcomes predicts only the price effect. Therefore, a model that allows medical care to improve health over the course of the year should predict greater medical care consumption in the uninsured state, producing a smaller moral hazard effect. Assumptions concerning an individual's knowledge of current and future price and health outcomes may affect estimated moral hazard effects as well. For example, if an individual does not know the total price of medical care prior to consumption, then loss of insurance coverage represents not only an increase in the out-of-pocket cost of medical care but exposure to greater uncertainty as well.[66] If an individual is risk averse, then his medical care consumption should respond more (negatively) to the loss of insurance coverage when he does not know medical care prices prior to consumption. As a result, a model that assumes medical care prices are unknown prior to consumption should produce larger moral hazard effects.

[66] Health insurance cost-sharing characteristics protect the insured by truncating the right tail of the medical care price distribution. For example, assume an insured individual knows that upon visiting the hospital he faces a total price of $500 with probability 0.90 or $2,000 with probability 0.10. Assuming a $300 deductible and $50 hospital co-pay, an insured individual faces a maximum out-of-pocket cost of $350. An uninsured (risk averse) individual is worse off than an insured individual for two reasons: he faces a larger expected out-of-pocket cost ($650) and receives disutility from exposure to the risk of a high price draw.

The within-year decision-making model allows medical care consumption to alter future health outcomes, assumes medical care prices are unknown prior to consumption, and allows for uncertainty about future within-year medical care price and health outcomes. The annual expenditure models of Cardon and Hendel (2001), Einav et al. (2013), and Kowalski (2013) are characterized by a health insurance decision at the beginning of a year, followed by an exogenous annual health shock, which is followed by an annual medical care expenditure decision.[67] However, an individual represented by the data used in estimation actually makes a series of daily medical care consumption decisions and receives multiple health shocks over an insurance year; thus, a number of assumptions are made implicitly in these models in order to aggregate behavior and outcomes up to an annual level. First, as the annual health outcome is assumed to be exogenously determined (i.e., independent of prior medical care consumption), so too are within-year health outcomes (assumption 1). Second, in order for a daily decision maker to be able to optimally determine his aggregated annual expenditure level, medical care prices must be known at the time of purchase (assumption 2). Third, the annual expenditure model assumes that all uncertainty is revealed prior to an expenditure decision. This assumption suggests that all health and price shocks that a daily decision maker receives over the course of an insurance year are known at the beginning of the year (assumption 3).

I use the within-year decision-making model and estimated parameters to calculate the effect of moral hazard under assumption 1 (simulation 1), under assumption 2 (simulation 2), and under assumptions 1, 2, and 3 (simulation 3); where the last set of assumptions is most representative of an annual expenditure model. The moral hazard effect is calculated by simulating the model twice for each set of assumptions: once assuming individuals hold their observed health insurance plans and once assuming they have no health insurance. To impose an assumption of exogenous monthly health transitions (assumption 1) on the within-year decision-making model, I update monthly illness states and general health status using a predetermined set of outcomes, rather

[67]Bajari et al. (2013) is similar but does not feature an insurance decision. Also, unlike the other papers listed, Bajari et al. allow for some uncertainty at the time of medical care consumption. The authors assume that an individual selects his total annual medical care expenditure while knowing the distribution of the proportion of that expenditure he must pay out-of-pocket, rather than the exact proportion.

than allowing illness and general health probabilities to be altered by medical care consumption.[68] In simulation, an individual still solves the optimization problem as if medical care is productive as the model's parameters reflect that this is the primary benefit of consuming medical care. To impose an assumption of price certainty prior to medical care consumption (assumption 2) on the within-year decision-making model, an individual receives one price draw for each type of medical care in each month, rather than integrating over the conditional distribution from which prices are drawn.[69] Perfect foresight (assumption 3) is imposed on the model by providing an individual with all future price, health, and preference shocks in the first month of the insurance year.

Without altering any assumptions of the within-year decision-making model, health insurance acquisition is predicted to increase mean annual medical care expenditures by 92%. (I refer to this simulation as the *preferred simulation.*) In simulation 1, assuming that within-year health transitions are exogenous increases the estimated effect of moral hazard to 100%, which is consistent with discussion above. In the preferred simulation, the probability of acute illness increases by 2.9% in the first three months (due to lower medical care consumption when uninsured), leading to an increase in medical care consumption throughout the remainder of the year.

In simulation 2, where prices are known prior to consumption, health insurance acquisition is predicted to increase mean annual medical care expenditures by 81%, which is consistent with the discussion above. In this simulation, the decrease in medical care consumption caused by the loss of health insurance is 14.5% for doctor visits, 44.4% for hospital days, and 1.7% for prescription drugs. In the preferred model, the decrease is 20.1% for doctor visits, 78.0% for hospital days, and 1.7% for prescription drugs. If the price paid for medical care were the same in simulation 2 as it is

[68]The predetermined set of illness and general health outcomes is taken from the simulation in Section 6.2 (i.e., simulation under normal conditions). Ideally, observed outcomes from the data would provide the exogenous transitions needed for simulation 2, as these outcomes would best reflect the assumptions of those modeling annual expenditure decisions under alternative insurance schemes. However, because general health status is not observed in every month in the data, this alternative set of outcomes is used.

[69]In practice, an individual actually receives one set of 12 price draws for each of the 3 types of medical care. Each of the 12 price draws corresponds to a specific combination of acute illness state, chronic illness state, and general health status. This strategy ensures that when an individual receives a high price draw he cannot simply wait for a lower price to arrive in the following month. A new set of prices is then drawn if his illness state or general health status changes. Note that in simulation 2, at any given time, an individual only knows the medical care prices that correspond to his current illness state and general health status. He does not know the price that he would face in another wellness state, nor does he know that prices will remain the same in the following month if his wellness state remains unchanged.

in the preferred simulation, then this consumption pattern would suggest a much larger difference in estimated moral hazard effects. However, because individuals in simulation 2 observe medical care prices, they strategically purchase medical care at lower prices when uninsured. The average price paid for medical care decreases by 7.5% for doctor visits and 63.8% for hospital days when individuals lose health insurance in simulation 2. In the preferred simulation, the decrease is 1.1% for doctor visits and 39.9% for hospital days.

In simulation 3, which most closely reflects the assumptions of an annual expenditure model, moral hazard is predicted to increase mean annual medical care expenditure by 74%. This estimate is smaller than the moral hazard effect produced by the preferred simulation (92%). The estimate is also closer to the moral hazard effects generated by annual expenditure models in the literature. The change in the price paid for medical care caused by the loss of health insurance in simulation 3 is almost identical to simulation 2. The root cause of the lower estimated moral hazard effect is that medical care consumption decreases more (in response to the loss of coverage) in simulation 2 than in simulation 3. The decrease in simulation 3 is 13.7% for doctor visits, 30.7% for hospital days, and 1.7% for prescription drugs. The decrease is greatest in the preferred simulation. In simulation 3, an individual solves a model where medical care is thought to not only improve his illness state in probability, but with certainty. Greater consumption when uninsured results, as some individuals consume more medical care (despite its cost) because knowledge of the illness shock ensures that the medical care will improve their illness state in the following month.

In summary, this research assumes that medical care decisions are made throughout an insurance year under conditions of uncertainty. This uncertainty makes medical care less valuable, as medical care consumption requires an individual to forgo a level of non-medical consumption that is known with certainty, in favor of an uncertain level of non-medical consumption and no guarantee of improved health. Health insurance reduces an individual's exposure to the financial risk that is associated with medical care consumption. When uncertainty at the time of medical care consumption is removed from an individual's optimization problem, medical care becomes more valuable, which leads an individual to consume more. An uninsured individual gains the most from the removal of uncertainty, because prior to removal he is exposed to the greatest level of risk. The burden of uncertainty when uninsured ultimately leads the within-year decision-making model to generate a larger moral hazard effect than what has been estimated previously in the literature.

6.3.2 Moral Hazard and Insurance Status

Among the many positive features of the MEPS data, the inclusion of both insured and uninsured individuals is of particular use in the study of moral hazard. In the U.S., the insured and uninsured populations have different observed and (likely) unobserved characteristics which may lead to differential responses to health insurance acquisition. Identifying this difference is important because the many of the key economic questions relating to moral hazard effects focus on either the insured or uninsured population, but not both. For example, to study the welfare implications of overconsumption caused by moral hazard, one must know how much more medical care the insured population consumes because of their insurance; however, the response of uninsured individuals to coverage is not relevant. In addition, to predict the increase in medical care consumption that would result from a strict individual health insurance mandate (100% coverage), one must have an estimate of how much more uninsured individuals consume once they become covered; however, the response of insured individuals to coverage is not relevant. The recent literature that studies moral hazard effects has utilized claims data (Bajari et al., 2013; Einav et al., 2013; Kowalski, 2013), which does not include the medical care consumption patterns of uninsured individuals, so moral hazard effects cannot be separated for the two groups.

I conduct a series of counterfactual simulations in order to study differences in how the insured and uninsured populations respond to insurance acquisition. First, I allow individuals to select health insurance optimally, as in Section 6.2, which identifies each individual as insured or uninsured. I then simulate behavior for each individual in an uninsured state and in an insured state, where the uninsured group from the first step is forced to select a plan, as in Section 6.3. I then calculate the response to insurance acquisition for the insured and uninsured groups. I find that the insured group increases mean annual medical care expenditure by 96% ($728 to $1426) and the uninsured group increases mean annual medical care expenditure by only 55% ($366 to $568).[70] As

[70] Finkelstein et al. (2012) find that previously uninsured individuals in Oregon increase their medical care expenditure by 25% the first year after gaining access to Medicare; Baicker et al. (2013) find an increase of 35% in the

expected, the differential response is driven by both observed and unobserved differences between the two sets of individuals. Table 12 shows that the uninsured are younger, poorer, more likely to be male, and, in this sample, enter the year in a better illness state. According to Table 4 males have significantly lower preferences for doctor visits and prescription drug consumption and Table 8 suggests that medical care consumption is lower when individuals are in a better illness state. Also, the uninsured are more likely to be of the unobserved type 2, which is associated with good health and low preferences for medical care.

These differences first lead uninsured individuals to purchase less generous plans when forced into coverage (they also choose from less generous alternatives sets). In comparison to the plans selected by the insured population, those wishing to remain uninsured select a plan that has a higher out-of-pocket premium; that is more likely to have a deductible and, conditional on having a deductible, has a larger deductible; that is equally likely to have a stop loss but, conditional on having a stop loss, has a larger stop loss; that has less generous doctor and hospital cost-sharing characteristics; and that is more likely to be a FFS type plan. The differential response to insurance acquisition between the insured and uninsured is driven in part by the less generous plan features that characterize the plans selected by the previously uninsured; however, the uninsured are less responsive to insurance acquisition independent of insurance selection. In another counterfactual simulation, I force all individuals into a common plan and calculate moral hazard effects separately for the insured and uninsured groups.[71] I find that mean annual medical care expenditure in the insured population increases by 66%; while mean annual medical care expenditure in the uninsured population increases by 47%.

As mentioned above, accounting for differential responses to insurance acquisition can be important for certain policy questions. For example, assume one is interested in how total U.S. medical care expenditure would be affected by a new health insurance policy that required all individuals to purchase coverage. There are several measures of moral hazard effects that could be taken from

second year.

[71] The common plan is a fee-for-service plan that has an annual out-of-pocket premium of $500, a deductible of $200, a stop loss of $1500, a doctor visit co-pay of $10, a hospital co-insurance rate of 15%, and a prescription drug co-insurance rate of 19%.

Table 12: Characteristics of the Insured and Uninsured

	Insured	Uninsured
Observed Characteristics		
male	0.48	0.53
black or hispanic	0.26	0.30
education	13.7	12.95
age	39.9	36.8
MSA	0.84	0.76
income	34728.3	26064.7
acute illness at $t = 1$	0.38	0.32
chronic illness at $t = 1$	0.38	0.27
poor health at $t = 1$	0.30	0.30
good health at $t = 1$	0.34	0.33
excellent health at $t = 1$	0.36	0.37
number of plans available	5.6	2.9
Unobserved Types		
type 1	0.09	0.01
type 2	0.56	0.75
type 3	0.17	0.09
type 4	0.18	0.15
Simulated Individuals	10,881	1,449

this paper, or outside literature, to predict the such a change in expenditure.[72] If one assumes that the average uninsured individual responds to coverage just as the average insured individual does, then the policy leads the previously uninsured to increase their medical care expenditure by 96%, which is \$43.2 billion (in 2011 dollars) of new spending.[73] This assumption would be required in order to use the estimated moral hazard effects of (Bajari et al., 2013; Einav et al., 2013; Kowalski, 2013), who only study insured individuals, to answer this question. If, on the other hand, one assumes that the average uninsured individual responds to coverage just as the average individual (independent of coverage status) does, then the policy leads the previously uninsured to increase their medical care expenditure by 92%, which is \$41.4 billion (in 2011 dollars) of new spending. However, if one fully account for the differences between the insured and uninsured populations, then the policy leads the previously uninsured to increase their medical care expenditure by 55%,

[72]The moral hazard effects estimated in this paper were not derived with objective of predicting actual changes in total U.S. medical care expenditure in response to a change in insurance policy. The estimation sample includes single, childless, employed individuals who get an insurance offer from their employer. However, this exercise exemplifies how even small differences in the estimated effects of moral hazard for different populations can lead to large differences in policy predictions.

[73]Average medical care expenditure among the 47 million uninsured U.S. citizens in 2011 was \$958 (in 2011 dollars, MEPS).

which is \$24.8 billion (in 2011 dollars) of new spending.

6.4 Counterfactual Experiment: An Individual Health Insurance Mandate

Among other things, the 2010 Patient Protection and Affordable Care Act (ACA) requires almost all U.S. citizens to carry a minimal amount of health insurance coverage.[74] This *individual mandate* is one of the more controversial pieces of the law. Proponents argue that forcing the (presumably young and healthy) uninsured into the market will help to indemnify the risk pool, subsidizing insurance premiums for the sick. Opponents worry that increased spending, due to moral hazard, will follow the increase in insurance coverage. Thus, in designing the individual mandate, policy makers must consider both the rate at which individuals who are currently uninsured will purchase coverage (for a given penalty) and the increase in medical care expenditure that results from the increase in coverage. The within-year model presented in this paper has the capacity to predict both of these outcomes.[75]

Under the ACA, an individual who is currently uninsured and receives an ESHI offer faces the following three alternatives: (1) purchase a plan through his employer, (2) remain uninsured and pay a penalty, or (3) purchase coverage privately (potentially thorough a newly formed health insurance exchange). In this policy simulation, I limit the alternative set to options (1) and (2).[76] Table 13 reports the predicted rates of health insurance take-up for a number of different penalties. Row 1 provides the predicted percent of the population that chooses to remain uninsured, despite receiving an ESHI offer, when there is no penalty for refusing coverage. Rows 2, 3, and 4 mimic

[74] Individuals with incomes below the tax filing threshold (\$9,750 for an individual in 2013) and those who cannot find coverage that costs less than 8 percent of their income are exempt from penalties imposed on the uninsured.

[75] This counterfactual implements the individual mandate provision of the ACA only. There are many other regulations that the ACA will impose upon the marketplace that are not considered. Furthermore, the empirical analysis conducted in this paper focuses on a population of individuals who are unmarried, childless, employed, between the ages of 19 and 64, and have the ability to purchase health insurance through their employers.

[76] Private health insurance is rarely purchased by individuals receiving an ESHI offer in the US because ESHI plans are generally subsidized by employers and receive preferential tax treatment. Health insurance that is provided to employees as part of a compensation package is not taxed by the US government. Plans purchased on the private market are paid for with taxable income. However, some single individuals who receive an ESHI offer will be eligible to enroll in a health insurance exchange and will qualify for tax credits. To purchase health insurance through a newly formed health insurance exchange, an individual's least expensive ESHI option must have an out-of-pocket premium that exceeds 9.8% of his income or his employer's premium contribution is less than 60% of the premium. To receive a tax credit, an individual's income must be between 100 and 400 percent of the federal poverty line (about \$11,490 to \$45,960 for a single individual in 2013).

the planned penalties that the ACA will enforce in 2014, 2015, and 2016, respectively. The 2016 penalty represents fully implementation of the policy. In 2014, an individual who does not possess the minimal level of health insurance coverage is required to pay a penalty of $95 (in 2014 dollars) or 1% of his income (whichever is larger).[77] The model predicts that the percentage of uninsured individuals will decrease in the first year from 11.8% to 9.6%, or that 81.7% of the previously uninsured individuals will remain uninsured. Rows 4 through 12 report the percent of individuals who remain uninsured given larger flat rate penalties, but holding the percentage of income penalties fixed at the 2016 level of 2.5%.

Table 13: Predicted Health Insurance Coverage Rate

Penalty			% Uninsured	% Remaining Uninsured
1996 dollars	2016 dollars	% of income		
0.00	0.00	0.0	11.8	100.0
61.82	95.00†	1.0	9.6	81.7
205.14	325.00‡	2.0	7.4	63.1
425.54	695.00	2.5	6.0	50.9
489.83	800.00	2.5	5.8	49.3
612.28	1000.00	2.5	5.1	43.3
734.74	1200.00	2.5	4.4	37.9
918.41	1500.00	2.5	3.7	31.8
1224.56	2000.00	2.5	2.9	24.4
1530.70	2500.00	2.5	2.2	18.6
1836.84	3000.00	2.5	1.6	13.5
2142.98	3500.00	2.5	1.3	11.0
2449.12	4000.00	2.5	1.0	8.8

† In 2014 dollars.
‡ In 2015 dollars.

The table offers two interesting findings. First, the planned penalty for 2016 (i.e., the greater of $695 or 2.5% of income) reduces the percent of uninsured individuals in the population from 11.8% to 6.0%. The demographic make-up of the uninsured population used in estimation and simulation make this take-up rate particularly important. The sample includes single, employed individuals, who are likely healthier and wealthier than the average uninsured individual in the population. Therefore, a high take-up rate for this subgroup is necessary for the success of the bill, which requires the healthy to purchase coverage in order to subsidize the premiums of the sick.

[77] To discount the penalties to 1996 dollars I assume an inflation rate of 3% for all years after 2013 and the average annual CPI inflation rate reported by the Bureau of Labor Statistics for years between 1996 and 2013.

The proportion of uninsured individuals could be further reduced below 3% of the population by increasing the flat penalty to $2000 (in 2016 dollars). Second, the table highlights the difficulty that policy makers face in producing universal coverage using an incentive-based scheme. As the penalty is raised, those who remain uninsured are the least sensitive to further penalties. For example, increasing the flat penalty from $1000 to $1500 (in 2016 dollars) decreases the percentage of uninsured individuals by 1.4 percentage points. As an additional $500 is added to the penalty repeatedly, the percentage of uninsured individuals decreases but at a decreasing rate: 0.8, 0.7, 0.6, 0.3, etc. If the goal is universal coverage, then an alternative policy of forced take-up (implemented by employers, who could be required to enroll employees in a default health insurance plan) may be preferable, but is not without consequence. Using the model and estimated parameters, I calculate the average expected welfare loss of among uninsured individuals from this policy to be $1608 (2016 dollars).[78] Note that this penalty is more than two times the fixed dollar penalty at full implementation.

I am also able to examine how total annual medical care expenditure responds to an individual mandate. Assuming premiums and medical care prices are unchanged, spending among previously insured individuals remains unchanged. Among previously uninsured individuals, mean annual medical care expenditure for the newly insured increases by 77% (moral hazard effect), while expenditure for those remaining uninsured falls by 2.4% (income/penalty effect). The net effect on the population as a whole is a 1.3% increase in medical care expenditure. This effect is small for several reasons. First, only 11.8% of the population is uninsured prior to the policy and are at all affected (under the assumption that medical care prices and insurance premiums are unaffected by the policy). Second, only half of these individuals acquire coverage and increase their spending. Third, the absolute level of mean spending among the newly insured is small relative to those previously insured ($637 vs. $1448, respectively).

[78] The average expected welfare loss is measured as the average penalty that would make an uninsured individual indifferent between remaining uninsured and paying the penalty or being insured and paying the premium.

7 Conclusion

In this paper, I study insurance-induced moral hazard using a dynamic model of within-year medical care consumption. An individual's optimization problem is defined by an annual health insurance decision, followed by a sequence of monthly medical care consumption decisions made over the course of a health insurance year. The within-year dynamic structure stands in contrast to existing work that examines the relationship between health insurance and medical care demand by aggregating medical care decisions up to an annual level. The disaggregated model of decision making more accurately describes the data generating process by allowing medical care consumption to alter future health outcomes, assuming medical care prices are unknown prior to consumption, and allowing for uncertainty about future within-year medical care price and health outcomes.

The effect of moral hazard on total annual medical care expenditure is calculated by simulating individuals' behavior under various insurance conditions. There are two main findings. First, the within-year model produces a moral hazard effect that is 24% larger than an alternative model that imposes the more restrictive assumptions of a typical annual expenditure model. Ultimately, the presence of uncertainty at the time of medical care consumption in the within-year decision-making model decreases the expected value of medical care consumption. The larger moral hazard effect is driven by low medical care consumption when uninsured, as risk averse individuals who face uncertainty are exposed to significant risk in consumption. Second, I find heterogeneous moral hazard effects across the population. Of importance to policy makers is that insured individuals are found to be much more responsive to coverage than uninsured individuals (96% vs. 55% increase in spending in response to coverage, respectively).

This research advances the economic literature on insurance-induced moral hazard by allowing for dynamic within-year incentives and uncertainty in a model of health insurance and medical care consumption decisions; however, this research could also benefit from additional data that would allow for the modeling of additional supply and demand side outcomes/behaviors. Supplementing the medical care consumption information that I observe with data on recommended courses of treatment for illnesses would allow one to disentangle the roles of doctors and patients in the medical care decision-making process. Furthermore, observing all employees within a firm (i.e., risk pools) may allow for insurance premiums to be determined in equilibrium, which would allow one to study how new insurance alternative sets affect insurance take-up, premiums, and medical care expenditure. These extensions are interesting both theoretically and empirically and are left for future work.

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A Appendix - Charts and Tables

Table 14: Representativeness of the Sample

	Whole Sample		Estimation Sample	
	mean	s.d.	mean	s.d.
age	36.88	12.21	39.56	11.70
education (highest grade completed)	13.40	2.53	13.62	2.46
income (in 1996 dollars)	30985.62	21432.55	33713.84	21953.46
male	0.53	0.50	0.48	0.50
lives in a MSA	0.84	0.36	0.83	0.38
Hispanic	0.14	0.35	0.12	0.33
black	0.16	0.37	0.14	0.35
federal employee	0.03	0.18	0.09	0.28
northeast	0.19	0.40	0.19	0.40
midwest	0.24	0.43	0.25	0.43
south	0.35	0.48	0.34	0.47
west	0.22	0.41	0.22	0.41
excellent health status	0.34		0.32	
good health status	0.35		0.35	
poor health status	0.31		0.33	
total annual expenditure †	1490.37	4033.53	1636.53	3063.95
insured all year	0.81	0.39	0.91	0.29
Sample Size	4859		1232	

† This expenditure level was take directly from the MEPS data and includes types of medical care spending not included in this analysis (e.g., dental and eye care, home healthcare, medical equipment, etc.).

Table 15: Structural Price Parameter Estimates

	Doctor Price		Hospital Price		Prescription Price	
	est.	s.e.	est.	s.e.	est.	s.e.
Price						
constant	4.2338	0.0695	6.0503	0.0315	4.4014	0.0608
male	0.0243	0.0189	0.0508	0.0537	-0.2485	0.0169
non-white (black or Hispanic)	-0.1183	0.0357	0.0061	0.0541	-0.0316	0.0155
education (highest grade completed)	-0.0338	0.0051	-0.0031	0.0165	0.0115	0.0035
age	0.0015	0.0011	0.0089	0.0016	-0.0001	0.0006
lives in a MSA	0.1207	0.0299	0.1294	0.1229	-0.0819	0.0173
income (in 1996 dollars)	0.0033	0.0006	0.0079	0.0041	0.0013	0.0004
March/April (indicator)	0.1841	0.0464	0.3457	0.1476	-0.0566	0.0329
May/June (indicator)	0.2524	0.0475	0.3244	0.1317	-0.1490	0.0329
July/August (indicator)	0.1513	0.0449	0.0075	0.0922	-0.1877	0.0340
September/October (indicator)	0.1204	0.0437	0.5808	0.1897	-0.1458	0.0327
November/December (indicator)	0.1330	0.0487	0.2732	0.1787	-0.0339	0.0251
HMO	-0.0856	0.0273	0.3182	0.1366	-0.1341	0.0149
PPO	-0.0195	0.0206	-0.0017	0.0205	0.0916	0.0258
no insurance	0.1237	0.0501	-0.7416	0.1593	-0.2526	0.0339
acute illness	0.0398	0.0254	-0.1495	0.1035	0.1290	0.0166
chronic illness	0.0072	0.0282	-0.2108	0.1289	0.2459	0.0220
less than excellent health status	0.4736	0.0480	-0.0130	0.0163	-0.1186	0.0356
less than good health status	-0.3800	0.0311	0.8883	0.1240	0.2674	0.0263
gamma shape parameter	1.2102	0.0204	0.5761	0.0371	2.0456	0.0226

Table 16: Initial Condition Probability Parameter Estimates

	Health Status		Acute Illness		Chronic Illness	
	est.	s.e.	est.	s.e.	est.	s.e.
Initial Condition						
constant	-1.1315	0.5323	-0.1575	0.7045	-2.4117	0.8227
male	0.3068	0.1369	-0.7126	0.1713	-0.5525	0.1859
non-white (black or Hispanic)	-0.2747	0.1444	-0.4252	0.1814	-0.2691	0.2125
education (highest grade completed)	0.0795	0.0292	0.0093	0.0374	0.0854	0.0428
age	-0.0204	0.0060	0.0032	0.0123	0.0585	0.0139
lives in a MSA	0.1176	0.1681	0.0568	0.2023	-0.1542	0.2340
income (in 1996 dollars)	0.0086	0.0043	0.0007	0.0053	0.0001	0.0055
March/April (indicator)	0.0860	0.2652	-0.5090	0.3144	*	*
May/June (indicator)	-0.0447	0.1978	-0.1933	0.3487	*	*
July/August (indicator)	-0.0163	0.2538	0.0248	0.2183	*	*
September/October (indicator)	-0.0756	0.2683	-0.4642	0.3147	*	*
November/December (indicator)	*	*	*	*	*	*
less than excellent health status	*	*	0.3630	0.3722	0.1831	0.4490
less than good health status	*	*	0.1765	0.3985	0.5640	0.5103
less than excellent health status*age	*	*	0.0014	0.0157	0.0137	0.0195
less than good health status*age	*	*	-0.0019	0.0159	-0.0053	0.0207
last year income	0.0459	0.0423	0.0167	0.0528	0.0569	0.0590
last year income missing	-0.0378	0.2854	-0.0395	0.3608	-0.0130	0.4043
veteran (indicator)	-0.1452	0.2242	0.2579	0.2765	-0.3692	0.3200
foreign born (indicator)	0.0406	0.2272	0.3385	0.2622	-0.6485	0.3189
cut-point	1.5432	0.0791	*	*	*	*

Table 17: Closing Function Structural Parameter Estimates

	Parameter	Estimate	SE
Closing Funtion			
doctor visits	γ_0	-0.1180	0.1220
hospital days	γ_1	0.4559	0.3368
Rx consumption	γ_2	-0.4420	0.2912
doctor visits^2	γ_3	0.0154	0.0130
hospital days^2	γ_4	-0.0102	0.0105
doctor visits*Rx consumption	γ_5	0.0265	0.0391
doctor visits*hospital days	γ_6	-0.1135	0.0812
hospital days*Rx consumption	γ_7	-0.0032	0.0369
doctor visits*age	γ_8	0.0012	0.0042
hospital days*age	γ_9	-0.0366	0.0161
Rx consumption*age	γ_{10}	0.0101	0.0131
acute illness	γ_{11}	-30.4658	6.7544
chronic illness†	γ_{12}	-200.0000	
less than excellent health status	γ_{13}	-57.5097	7.6595
less than good health status	γ_{14}	-64.9785	7.4035

† Parameter is not currently estimated.