A Dynamic Sequential Model of Health Insurance and Medical Care Consumption Decisions

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INCOMPLETE

Abstract

This paper develops and estimates a dynamic, stochastic, discrete choice optimization problem that illustrates individual healthcare purchasing behavior over a health insurance year. In the problem, agents first select a health insurance plan and then make a series of medical care decisions conditional on their coverage. Because consumption of care is modeled sequentially, rather than as an annual decision, the model captures changes in medical expenditure behavior over the year as consumers experience stochastic health shocks and pass discontinuities in the medical care price distribution created by cost-sharing features of the insurance plan. Further, a backwards recursion solution technique allows forward looking agents to form expectations about their future medical care expenditure under each insurance alternative before selecting coverage. Estimation of the models structural parameters will speak directly to several important theoretical issues often discussed in healthcare literatures, including consumer responsiveness to “effective” as opposed to “marginal” medical care prices, insurance induced moral hazard, and adverse selection into health insurance plans. Also, counterfactual experiments will be performed, testing the impact of several potential national health insurance policies (such as a public option, insurance exchanges, expanded employer choice sets, etc.) on medical care expenditures and health in the United States.
1 Introduction

An ever growing problem in the United States is the rising cost of healthcare. From 1960-2009, national healthcare expenditures have grown from 5.2% to 17.6% of GDP. Some have cited an increase in the proportion of medical care costs paid by insurers over the same period (from 27.3% to 71.1%) as evidence that a diminished financial responsibility of patients may explain at least part the problem. The recent passing of the Patient Protection and Affordable Care Act, which (1) mandates that nearly all US citizens have health insurance and (2) states that one of its two primary objectives is cutting healthcare expenditure, makes it apparent however that not all economists and policy makers agree that more insurance leads to more expenditure.¹ In truth, our understanding of this relationship is derived mostly from theory alone. Inefficient data and the complexity of modern day health insurance plans have caused many empirical researchers to avoid estimating dynamic decision making models that are consistent with economic theories of consumer behavior. This paper will estimate such a model using a confidential data set in hopes of bettering our understanding of the relationship between health insurance and medical care demands.

To investigate this relationship, I develop and estimate a dynamic, stochastic, discrete choice optimization problem that describes individual healthcare purchasing behavior over a health insurance year. The problem is based on Keeler, Newhouse, and Phelps’s (1977) theory of consumer medical care demand that recognizes care as a unique good due to consumer uncertainty of future demand and prices that vary with the number of units purchased. In the model, medical care utilization is determined through a series of sequential decisions made over the year, rather than one annual decision, as is often done in the literature. The benefit of this structure is two-fold. First, the approach allows for a more realistic decision making process as individuals make healthcare choices sequentially in response to and in anticipation of current and future health shocks. Second, the technique allows one’s health insurance plan to affect medical care consumption behavior by changing the price of care. More specifically, the cost sharing characteristics of modern day health insurance plans often create non-linearities in the price of medical care.² These discontinuities in the price distribution are a function not only of plan characteristics but of past expenditure as well. Thus, as expenditure accumulates over the health insurance year, the price of care may change in accordance with one’s insurance plan, altering purchasing behavior.

The model is solved using a backwards recursion method that discounts the insurance-conditional value of medical care consumption in each period to the beginning of the year. This value is then used by

² Examples of these features are deductibles, co-insurance rates, co-pay amounts, and maximum out-of-pocket expenditure levels.
individuals in selecting their optimal health insurance plan from a set of alternatives provided by their employer. Relative to other papers in the health insurance choice literature, this technique is favorable because it uses actual consumer health outcomes, purchasing behavior, and prices to form expectations of future expenditure under each plan. The more popular alternative is simply modeling the indirect utility gained from insurance as a function of plan features and personal characteristics to proxy for this expected future expenditure (Feldman et al., 1987).

Estimation of the model’s structural parameters will allow for examination of several popular topics in both the health insurance and medical care demand literatures. First, because I explicitly account for the “effective” price of medical care, generally omitted within-year stochastic health shocks, and the endogeneity of accumulated within-year medical care spending, I will be able to test the validity of Keeler, Newhouse, and Phelps’s (1977) theoretical predictions. Specifically, estimates will allow me to examine the relationship between medical care consumption, the remaining amount of spending needed to reach one’s deductible, and the amount of time until the end of the period. Second, controlling for unobserved heterogeneity common to insurance and medical care decisions will allow me to look for evidence of adverse selection and simulate estimates of moral hazard. Not only is the estimation technique able to separate these two forces, but it will provide the first estimates of this kind where medical care expenditure accumulates over the health insurance year as the result of sequential decision making, rather than resulting from an annual expenditure decision. It will be made clear in Section 2.3 why the latter of these two strategies could lead to bias results. Third, the model is particularly well suited for counterfactual policy experiments, especially those testing the impact of new national health insurance systems, because medical care decisions, medical care prices, and several measures of health are all explicitly modeled. Possible experiments include, but are not limited to, predicting the change in medical care expenditures and health that would arise from the creation of public health insurance exchanges, gauging the popularity and effectiveness of a public health insurance option, evaluating the impact that a forced expansion of employer provided insurance offer sets would have on welfare, etc.

The model’s parameters are estimated using data from the 1996-1999 Medical Expenditure Panel Survey (MEPS) which is collected by the Agency for Healthcare Research and Quality (AHRQ). These data are unique because they contain detailed information about all employer subsidized health insurance plans offered to a national sample of employed individuals, as well as a dynamic history of medical conditions.

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3 Effective price is a term used by Keeler, Newhouse, and Phelps (1977) to describe the marginal cost of medical care treatment plus some bonus associated with being closer to reaching one’s deductible, and therefore experiencing low prices in the future. This idea will be explained thoroughly in the next section.
and medical expenditure over a two year span. Each of these elements is critical to estimating a model containing both insurance and medical care decisions in a dynamic framework.

The remainder of the paper is structured as follows: Section 2 gives an extensive review of the literature relating to these topics. Section 3 provides a theoretical explanation of an individuals’ decision making process with regard to health insurance and medical care. Section 4 describes the survey used in data collection, briefly discusses sample determination and sample size, and lists some data problems that I will face moving forward. Section 5 offers some preliminary sample means and correlation observations that suggest desired empirical relationships. Section 6 begins to discuss some empirical heroics I may attempt.

2 Literature review

*Since last presenting, I have focused most of my energy on gaining a better understanding of the literature and figuring out where this paper fits in. As a result, you will notice that this section is quite lengthy. I promise I will condense this before the next time I present, but I wanted to include this exhaustive version to (1) show what I’ve been doing and (2) get all my thoughts down on paper. If reading it interests you, then knock yourself out. If you think your comments would be more helpful on the model or data, then that’s great too.

The model and estimation objectives proposed above have been influenced by work from several lines of literature inside and outside of health economics. As such, below I separate the discussion of previous work as follows: First, I detail a history of theoretical work on consumer behavior in medical care markets that has significantly impacted the construction of the consumer optimization problem found in this paper. Second, I dedicate three sub-sections to expanding upon each of the empirical objectives described above. In these discussions I explain how estimating a theoretically consistent model of consumer behavior can improve estimates and predictions found in existing work.

2.1 Theories of Consumer Behavior in Health Economics:

Economic interest in the relationship between health insurance and medical care demands was popularized in the early 1960’s by Arrow (1963). Arrow’s paper described the (now) popular concept of moral hazard, or the tendency for medical care demand to rise as a result of widespread medical insurance. The work also briefly mentions the difficulty that insurers face in pricing plans due to the informational advantage that consumer’s have in predicting their future health. This idea was further discussed in Akerlof’s (1970) seminal paper “The Market for ‘Lemons’” where he coined the consumer’s informational advantage as a problem of adverse selection. Unfortunately, these ideas were purely
descriptive as neither paper developed a theoretical model of consumer decision making that would justify the behavioral predictions.\(^4\)

The first widely respected formal model of consumer healthcare demand was introduced by Grossman (1972).\(^5\) In formatting this model, the author hoped to integrate the following three ideas: (1) People demand health and medical care affects health; therefore, the demand for medical care is a derived demand. (2) People don’t buy health, they produce it. (3) Health depreciates, but not immediately. These three critical observations help Grossman develop the concept of health stock; an all-encompassing measure of individual health that acts as a production and consumption good. While Grossman’s model is highly respected and is often cited as the benchmark theory underpinning many empirical works in the health economics literature, it fails to include health insurance as a key determinate of medical care prices.

Keeler, Newhouse, and Phelps (1977 – KNP henceforth) can be thought of as an extension of Grossman’s model that allows insurance to have an important influence on the demand for medical care. Most notably, KNP recognize two features of the medical care market that make demand for the good unique. First, insurance causes the marginal price of medical care to vary with the number of units purchased.\(^6\) Second, future demand for medical care is uncertain because health is uncertain. The authors explain that the unique combination of these two features forges a divide between the marginal price of medical care and the effective price, or the price that influences consumer decision making. The effective price of a unit of care can be thought of as the marginal price minus a bonus, where the bonus is the amount that a consumer is willing to pay to move closer to their deductible and thus a lower price of care in the future.

KNP’s formal model alters Grossman’s by: (1) dividing a year into smaller periods; (2) establishing the possibility for stochastic, non-persistent illnesses within the year; and (3) introducing a deductible to the budget constraint.\(^7\) Assuming rational expectations, the authors solve the model to show that individuals will consider not only the marginal price of care when making medical care decisions, but also the effect

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\(^4\) For more on moral hazard and adverse selection, see section 2.3 or read Cutler and Zeckhauser (2000) for an excellent summary of concepts, past work, and empirical strategies in identification.

\(^5\) In response to Arrow (1963), Pauly (1968) developed a very basic model of medical care demand that showed (more formally) that the increase in medical care consumption resulting from insurance could be explained very simply by an inelastic demand for care. It should be noted that the objective of this work was to give a practical explanation to the moral hazard phenomenon and not to fully explain the consumer’s decision making process.

\(^6\) A plan with a deductible and a co-insurance rate, for example, would cause this. Prior to reaching the deductible (a level of total annual expenditure designated by the insurance plan) the consumer is responsible for paying the full price of care. After crossing the deductible, they are required to pay only a proportion of the price (this is called the co-insurance rate). Thus, an individual would face two different prices for identical treatments before and after reaching the deductible.

\(^7\) For simplicity, they omit a co-insurance rate or co-pay level, assuming that the marginal price of care is zero after reaching the deductible.
that consumption will have on the future price of care. Further, the model leads to the following two testable results: first, expected medical care consumption is decreasing in the amount of spending needed to reach one’s deductible, *ceteris paribus.*

8 Second, prior to reaching one’s deductible, expected consumption is increasing in the amount of time left until the end of the year, *ceteris paribus.* A graphical depiction of this relationship can be seen in Figure 1.

The behavioral model found in this paper is built on principles established in Grossman (1972) and KNP (1977). As will be seen in Section 3, I extend their work by allowing for multiple types of illness, care effects and persistence in illness, multiple types of medical care consumption with appropriately different marginal prices, uncertainty in current and future marginal prices, and a more robust budget constraint that accounts for the complexity of modern day health insurance plans. It is my hope that these modifications do well in further characterizing the intricacy of the consumer’s problem and in expanding the scope of the models empirical capabilities.

2.2 *Empirical support for KNP (1977):*

One of the stated objectives of this paper is providing support for the theoretical findings of KNP (1977). More specifically, I hope to show that medical care consumption is decreasing in deductible remaining and increasing in time remaining in the year. Understanding this result is important for several reasons. First, In order to design optimal insurance plans insurance providers and governments need to understand how individuals react to deductibles and maximum out-of-pocket expenditure levels that create non-linearities in the medical care price schedule. Because KNP predict that deductibles impact not only the level of expenditure but the timing as well, verifying their result may warrant future research into features such as moving deductibles (deductibles that adjust with the time left in the insurance period). Second, as is explained in KNP, if individuals respond to effective prices instead of marginal ones then any paper estimating price elasticity of medical care demand by regressing annual consumption on average prices, marginal prices at the end of the year, or average fraction of expenditure paid will find bias estimates.

I am presently unaware of any paper that empirically verifies KNP’s theoretical predictions using a model that explicitly accounts for the effective price of medical care by correctly controlling for accumulated within-year medical care spending and expected future demand, which are both endogenous. Newhouse, Rolph, Mori, and Murphy (1980) examine the relationship between annual medical care expenditures and annual deductibles. They find that annual expenditures are decreasing in the size of one’s deductible, but the marginal impact of a dollar increase in deductible diminishes as it grows larger. Unfortunately, these

8 For the remainder of the paper, I will refer to the “amount of spending needed to reach one’s deductible,” as the “deductible remaining.”
findings can only suggest that lower annual deductibles increase the absolute level of consumption, which could be due to income effects, marginal price effects, or responsiveness to the effective price prior to reaching the deductible. Ellis (1986) uses a different approach in examining KNP’s prediction. He builds a theoretical model similar to KNP and then proves via simulations that the expected end-of-the-year marginal price of medical care is a good approximation of the effective price. Ellis then estimates much simpler reduced form Tobit models where medical care consumption in the first 30, 60, and 90 days of the year are written as functions of predicted end-of-the-year price. Results show that end-of-the-year price negatively impacts consumption in the first two periods, which is consistent with KNP. The result, however, is only shown for ambulatory mental health consumption and assumes that health is exogenous and predicted perfectly over time by consumers.

Keeler and Rolph (1988) use data collected from the RAND Health Insurance Experiment (HIE henceforth) to examine KNP’s results. The RAND HIE was a large federally funded experiment focused on understanding the relationship between health insurance, prices, and medical care demand. Individuals from seven cities across the United States were randomly assigned to 1 of 14 health insurance plans that differed primarily by a co-insurance rate and a maximum out-of-pocket expenditure level (MOX henceforth). A large benefit to using HIE data is that random assignment of plans greatly simplifies estimation of medical care demand because it ensures that insurance cost sharing features that impact the marginal price of care are not endogenously determined. The authors use these data to estimate the impact of MOX remaining on consumption behavior. To do this, they first divided the HIE claims data into episodes of treatment and further divided these episodes into those occurring when an individual was far from their MOX, was near their MOX, and was past their MOX. They then regress the number of visits per episode (and expenditure per episode) on co-insurance, predicted consumption under full insurance, and exogenous personal characteristics. According to the authors, finding different estimates for the co-insurance elasticity of demand between the three groups would provide support for KNP. They

9 Income effects in that for the same sequence of illnesses episodes a higher deductible makes one poorer because the full price of care is paid for more visits. This could lead to less annual expenditure because one is poorer after reaching the deductible. Marginal price effects in that for the same sequence of illnesses a higher deductible makes one face the (higher) total cost of care longer than they would with a lower deductible. This could lead to fewer visits and thus lower expenditure.

10 An MOX is a dollar amount associated with an insurance plan, such that if one’s accumulated annual out-of-pocket expenditure passes that amount, then all additional medical care consumption for the rest of the year is free. For more on why the endogeneity of insurance possession complicates medical care demand estimates, see Section 2.3 or Chiappori and Salanie (2003).

12 One group of individuals included in the HIE was randomly assigned full insurance, meaning all care was paid for in full. The authors used the relationship between total number of visits and exogenous characteristics for the sample of individuals having full insurance to predict consumption under full insurance for those without full insurance (it can be assumed that the groups are identical because plans are randomly assigned). Predicted consumption under full insurance was included to help control for the endogenous selection of individuals into the three spending remaining until MOX is reached groups.
did not find significant differences in these estimates. Unfortunately, there are several issues that threaten the validity of these findings. Most importantly, it is imperative to their results that predicted consumption under full insurance is estimated well as this helps control for selection into the three MOX groups and omitted future expectations of consumption. Given the limited number of independent variables used for estimation and low $R^2$’s, there is reason to believe predicted consumptions under full employment is not well estimated. Further, the model assumes that price effects are constant within MOX groups, episode occurrences are independent over time, and likelihood of an episode is constant and exogenous over the health insurance year. The first of these is not consistent with KNP, the second ignores the existence of chronic conditions, and the third doesn’t allow medical care to improve health.\footnote{Keeler, Buchanan, Rolph, Hanley, and Behoussin (1988) is a book that analyzes medical care demand by treatment episode, rather than by annual expenditure, using data from the HIE. While I have yet to read this book, I know that their estimation techniques do not use the concept of an “effective price” of care, as KNP suggest. As such, these results will continue to have the same problems that the other papers described above have: (1) spending needed to reach one’s deductible is endogenous and (2) health during the health insurance year is ever changing and is influenced by past medical care consumption. Because of these issues, deductible remaining and health will always be endogenous.}

2.3 Moral Hazard and Adverse Selection:

The second stated objective of this paper is improving existing estimates of moral hazard and providing support for/against the existence of adverse selection. As such, below I define each term, discuss why they are important, explain the difficulty in identifying them empirically, and review the literature. For a more complete discussion of these topics, see Cutler and Zeckhauser (2000).

By and large, the most popular research questions regarding the empirical relationship between health insurance and medical care demands involve the concepts of moral hazard and adverse selection. Each of these terms have precise definitions in contract theory, but are used rather loosely in health care literatures. For general discussion, I borrow Arrow’s (1963) definition of moral hazard, “as the incentive of individuals to have higher health expenditures when insured.” Adverse selection, on the other hand, arises from the informational advantage that consumers have over insurers with regard to knowledge their level of risk. As such, Akerlof (1970) explains that insurers should be unable to offer plans to individuals at an actuarially fair premium and must resolve to sell a fixed number of plans at the average (expected) cost of insuring. This pricing scheme results in adverse selection, or sicker individuals being attracted disproportionately to more generous plans and healthier individuals away from generous plans.

Studying these two forces is important because evidence of their presence suggests different policy actions. Cutler and Zeckhauser (2000) explain that moral hazard in medical care markets creates a fundamental trade-off between risk-spreading and generosity. If insurance leads individuals to consume
more, then optimal insurance policies will include cost-sharing measures, like deductibles and co-insurance. However, including these features in insurance plans shifts risk burden from risk-neutral insurers to risk-averse consumers, which is counter to the purpose of insurance. Consistent estimates of moral hazard are therefore important in designing insurance plans that optimally balance removing risk from consumers with not promoting over-consumption. According to Culter and Reber (1998) adverse selection is problematic because it works at odds with competition. On the surface, competition in insurance markets is good because it keeps prices down and allows individuals to choose plans that meet their preferences. However, if individuals select into plans based on private information then competition (i.e. a larger, more diverse choice set) encourages further selection. Rothschild and Stiglitz (1976) show that adverse selection can potentially eliminate the possibility for a competitive equilibrium in insurance markets, which can result in market failure. As such, policy should discourage competition if adverse selection does exist and promote competition if it does not.

Identification of moral hazard and adverse selection has been a popular empirical endeavor for researchers in a variety of contract markets since the 1980s. Early work focused mostly on the challenge of separately identifying the two forces. Chiappori and Salanie (2003) give an excellent summary of these difficulties and the most popular methods of identification. Some more recent work has focused on separately identifying different ways by which insurance may induce higher expenditures (Khwaja, 2001 and Karlan and Zinman, 2007), separating the effects of adverse and advantageous selection (Fang, Keane, and Silverman, 2006; Cutler, Finkelstein, and McGarry, 2008; and Keane and Stavrunova, 2010), and measuring welfare implications of adverse selection.

Chiappori and Salanie (2003) explain that there are four ways to identify adverse selection and moral hazard. The first is through joint estimation of an insurance choice and demand equation. Allowing correlation between the error terms in each equation captures the role that asymmetric information (which encompasses adverse selection and moral hazard) plays on decisions. Using this method, the two forces cannot be separated (see Chiappori and Salanie, 2000). The second is through natural or controlled experiments (see Manning et al., 1987 or Karlan and Zinman, 2007). The third is through structural estimation (see Cardon and Hendel, 2001). The fourth uses dynamic contract data in markets where contract premiums are experience rated (see Israel, 2004). Because health insurance plans in the U.S. are rarely experience rated, this last method is not an option.

It is important to distinguish this paper from those measuring the welfare implications from adverse selection. Because adverse selection simply describes individuals choosing plans based on private information about their risk type, it is very difficult to quantify a magnitude of selection. As such, this paper does not attempt to do so, simply opting to look for evidence of any adverse selection. There is a separate and very interesting line of literature pioneered by Cutler and Reber (1998) that somewhat addresses magnitude by measuring the impact that adverse selection has on welfare in specific insurance markets. These papers differ from this one in that they typically model changes in insurance premiums and insurance offerings in response to some exogenous event, in addition to consumer demand for insurance. By then assuming that changes in premiums and offerings after the event were caused by adverse selection, they can measure the impact that these changes have on welfare. Unfortunately, these papers often must assume no moral hazard for empirical tractability. For more on this literature, see Carlin and Town (2007), Eivin Finklestein, and Levin (2009), Eivin, Finklestein, and Cullen (2010), Bundorf, Levin, and Mahoney (2010), and Handel (2010).
This work fits into a group of papers within the health economics literature that strive to (1) measure the extent of moral hazard; that is, how much more medical care do individuals consume as a result of health insurance and (2) identify the presence of adverse selection.\footnote{One should not think of the identification of adverse selection as being a primary goal of this paper. Rather, because insurance choices must be modeled in order avoid endogenous plan features in the medical care demand equation, adverse selection is identified naturally by the estimation technique. As such, I will report my findings, but plan on spending much more time analyzing moral hazard estimates.} The biggest complication in studying this topic is limited data. Estimating moral hazard using a theoretically consistent model of consumer behavior, like KNP (1977), requires knowledge of every coverage and cost-sharing feature of every plan taken and declined by an agent; all medical care consumption information, including number of visits, types of visits, total cost of each visit, and type of treatment; some measure of health stock that transitions over time; the date and duration of every illness episode over the health insurance year; and general characteristics of the agent. In the past, the necessary insurance information has restricted researchers to firm level data (Dowd et al., 1991 and Bajari et al., 2011), Medicare recipients (Khwaja, 2001), or the RAND HIE where insurance is exogenous (Duan et al., 1983 and Manning et al., 1987).\footnote{Cardon and Hendel (2001) is the lone exception here as they use data from the National Medical Expenditure Survey (NMES), which includes employer insurance information.} After this, the remaining requirements make finding data especially difficult. The firm level information can be useful if it includes claims data, which is likely for self-insuring firms. However, firm data typically includes few personal characteristics, family information, or anything about employee health. Also, results derived from firm level data are the least generalizable. The Health and Retirement Survey (HRS), which gives one the ability to study Medicare recipients, only includes expenditure and health information once every two years. The Medicare Current Beneficiary Survey (MCBS) includes claims data but doesn’t contain illnesses incidents when individuals do not seek care. The RAND HIE contains information on decision makers from roughly 30 years ago and therefore may not represent more recent behavioral trends and treatment types. It also does not give one the opportunity to study adverse selection, as plans are assigned and not chosen.

In response to these data limitations, researchers studying moral hazard and adverse selection have repeatedly built both structural and reduced form models of medical care demand where (1) annual medical care expenditure is modeled as a one-time decision and (2) agents experience no change in their health state over the course of the year. The benefit of such models is that they require less data, are easier to estimate, and are easier to interpret. Theoretically, these models are problematic because individuals do not determine their annual medical care expenditures all at once; rather, annual medical care expenditure is an outcome that results from a sequence of consumption decisions and often a variety of different
prices. Further, as I will discuss below for several popular estimation techniques, moral hazard estimates generated using models of annual expenditure decisions are likely bias in an unpredictable direction.

There are two problems that consistently arise in empirical papers of moral hazard that are likely to bias results. First, is the inability of many annual expenditure models to correctly control for discontinuities in the medical care price distribution created by insurance characteristics like deductibles. Second, is the inability of these models to control for omitted current and future stochastic health shocks. The literature can be easily separated into those papers estimating reduced form parameters and those estimating structural parameters. The most widely recognized reduced form estimates of moral hazard come from papers using the RAND HIE data (Duan et al., 1983 and Manning et al., 1987). These papers estimate co-insurance elasticity rates using two- and four-part models of annual medical care expenditure. Fortunately, they are able to avoid potential bias introduced by deductibles because the randomly assigned plans of the HIE did not include deductibles. These authors do not, however, account for omitted health shocks that influence consumption. This could create bias if low co-insurance rates lead agents to consume more preventative and curative medical care early in the health insurance year, because they are then likely to incur fewer and weaker negative health shocks later in the year. Because negative health shocks are likely to encourage more consumption and they are potentially correlated with the co-insurance rate, then it is possible that co-insurance elasticity estimates are bias.

Dowd et al. (1991) uses a reduced form model to jointly estimate insurance and annual trips to the doctor, where demand for doctor visits is constructed as a linear function of plan deductible and co-insurance rate. In addition to having the same problem of omitted health shocks described above, the author’s technique assumes that deductible and co-insurance have a constant linear effect on the number of visits. This is likely a poor assumption as one’s deductible is apt to have some impact on visits when total expenditure is below the deductible, but no impact on visits after expenditures exceed the deductible. Further, the marginal impact of one’s coinsurance rate should be much stronger after reaching the deductible than before. Again, these issues are likely to lead to bias estimates of moral hazard.

Cardon and Hendel (2001), Khwaja (2001), and Bajari et al. (2011) all estimate structural models of annual medical expenditure decisions. In each, authors construct annual utility as a function of general

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18 The plans do include MOX levels, but the authors argue that they were high enough such that elasticities could be estimated for expenditure far below the level where the MOX likely did not impact decisions.

19 Another potential for bias here is due to the fact that some selection was present in the RAND data. Participants were randomly assigned these plans but were not forced to participate if they did not like their draw. Thus, many participants receiving less generous plans exited the sample immediately (25% of those getting the worst plan left the sample). Because those with poor expected health were more likely to leave the sample upon getting a less than generous plan, omitted health shocks are again correlated with co-insurance rates.
consumption $x$ and some function of annual medical care expenditure $f(m)$; such that $U = u(x, f(m))$. Each paper also writes general consumption in a format similar to the following:

$$x_t = y_t - p_j - g_j(m)$$

where $y_t$ is annual income, $p_j$ is the annual out-of-pocket premium for insurance plan $j$, and $g_j(m)$ represents a plan specific function determining annual out-of-pocket medical care expenditures as a function of total annual expenditures. While each of these papers specifies the function $g_j(\cdot)$ differently, they all do it in a manner that allows for the proportion of medical care consumption paid out-of-pocket to fall as total expenditure rises. While their structures do not necessarily have the capability of predicting discontinuous jumps in medical care prices, which one needs to fully represent behavioral responses to deductibles and MOX levels, this approximation does a reasonably good job of representing the impact that a deductible can have on out-of-pocket expenditure, and thus behavior.

Like the reduced form models discussed, the estimates generated in these papers are likely biased however due to their failure to control for stochastic health shocks. Again, bias will arise if medical care consumption, which is impacted by one’s insurance plan, affects future health shocks, and thus future consumption. Interestingly, the theoretical predictions of KNP (1977) suggest that one cannot even assign a direction to the bias. This is because we cannot be for sure how one’s deductible/plan alters the timing of care consumption within the year. KNP predicts that the introduction of a deductible has opposing effects on the likelihood of early consumption. At the beginning of the year, the average individual must spend a lot in order reach their deductible, implying a low likelihood of early consumption. Also at the beginning of the year, the average individual is below their deductible and far from the end of the year, implying a high likelihood of consumption. Thus, even if one is willing to assume that all care consumption leads to better health, because one cannot predict how deductibles impact the timing of consumption, a direction cannot be assigned to the bias.

The estimation technique in this paper avoids these problems by modeling sequential medical care decisions rather than annual expenditure decisions. In doing so, I will be able to capture a more realistic effect of deductibles, MOX levels, and other insurance characteristics on the budget constraint, which should better represent consumer behavior. Further, modeling stochastic health shocks over the insurance year explicitly will allow me to avoid the omitted variables problem present in all of the above papers.

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20 Interestingly, these three models are very similar to the one proposed in KNP (1977) when future demand for medical care is not unknown. In other words, these models should do a great job of estimating moral hazard if individuals know exactly how their health will transition, and thus how strong demand will be, over the year.
2.4 Policy Experiments:

The most widely cited benefit of estimating structural parameters, and potentially the most exciting opportunity for this work, is the ability to conduct counterfactual policy experiments. In addition to potentially improving upon other’s estimates of moral hazard, a key advantage that this model has over those discussed above is its ability to test the implications of new national health insurance policies. The advantage stems from two features of my model: (1) individuals choose their plan, rather than it being assigned to them (unlike the RAND studies) and (2) the motivation for selecting a plan is based solely on the plans characteristics, not a plan fixed effect (unlike Khwaja, 2001 and Bajari, 2011). Thus, in my experiments I can propose entirely new insurance offer sets – i.e. a health insurance exchange; change one or more characteristic of every plan in the existing offer sets – i.e. creating a national minimum deductible; introduce a new plan to everyone’s offer set – i.e. a public option; or even introduce a new insurance feature that is not included in the model – i.e. a health savings account. Then, through simulation, I can observe how medical care expenditure and health change to evaluate consumer welfare.

3 The Model

This section describes a dynamic programming problem in which single, employed individuals make a series of healthcare decisions to maximize lifetime utility.\(^{21}\) The flow of time is separated into two types of discrete periods, years, \(y\), and periods within years, \(t\). At the beginning of each year, a forward-looking agent is offered an exogenous set of health insurance alternatives by her employer.\(^{22}\) Before the start of the first period, she chooses the plan that maximizes her lifetime discounted future utility. This utility is a function of, among other things, optimal medical care behavior within the year conditional on coverage. In this paper that behavior is modeled explicitly over a series of periods.

\(^{21}\) The model is restricted to include only employed individuals who get an insurance offer from their employer because I only have insurance information for these individuals. While this does create some problems in generalizing these results, the issue should not be too alarming given that 57% of the non-elderly population in 2009 obtained their insurance through their employer (19% uninsured, 19% government insured, 5% privately insured). http://facts.kff.org/chart.aspx?ch=1850

\(^{22}\) The assumption that one’s health insurance offer set is determined exogenously is clearly not ideal. Some individuals obviously select their job based at least partially on the health insurance that they will be offered. However, modeling one’s choice into a particular job, with particular health insurance options would require an unfathomable amount of data. Thus, this exogeneity assumption has become the norm in the literature. One type of “solution” to the problem would be modeling an agent’s choice into an insurance offering job (which I have the data for).
At the beginning of each period, the agent learns of her acute and chronic health states before making a medical care utilization decision. These health states evolve stochastically throughout the year and are influenced by past health and care consumption. Medical care comes in two forms, doctor’s office visits and hospital stays, which have different prices and can potentially influence future health in different ways. In purchasing medical care consumers pay an out-of-pocket price. This price is a function of the true price of care, accumulated expenditure within the coverage year, and the characteristics of their health insurance plan. Further, it is assumed that the true cost of care is stochastic over time and even unknown at the time of consumption. After making a medical care decision, the agent’s health stock (or overall health level) is updated before transitioning into the next period.

The remainder of this section further explains the details of this model. First, I describe the annual insurance and per-period medical care decisions that the agent makes. Second, each of the stochastic elements that the agent forms expectations over when making their decisions is explained. Third, I describe the agent’s optimization problem by formulating a per-period utility function and budget constraint. The section closes with the solution to the optimization problem, revealing an optimal per-period and annual decision rules for the agent.

3.1 Annual and Per-period Choices

At the beginning of each year, \( y_i \), individual, \( i \), selects health insurance from an exogenously determined set of employer subsidized plans, \( J_i \), which is a subset of the master set of plans, \( J \). Because these data contain individuals who are employed by many firms across the United States, plans must be generalized; otherwise, \( J \) would be made up of several thousand plans, most of which only being offered to one employee. A plan is therefore entirely defined by its annual premium, \( P \); annual deductible, \( D^1 \); maximum annual out-of-pocket expenditure, \( D^2 \); hospital co-insurance rate, \( C^{h1} \); hospital stay co-pay level, \( C^{h2} \); doctor’s office co-insurance rate, \( C^{d1} \); doctor’s office co-pay level, \( C^{d2} \); and the amount by which the plan restricts coverage to net-work of physicians (HMO, PPO, or open), \( N \).\(^{23}\) By then

\(^{23}\) Some plans in the data do not fall into this convenient structure. About 2% of plans specify hospital co-pay amounts by day instead of by stay. For these plans, I multiply the co-pay amount by 5, which is the average hospital stay length. Also, about 40% of plans have 2 deductibles, one for hospital visits and one for doctor office visits. For
discretizing each variable and defining an insurance bin, $j$, for every combination of the variables’ discretized values, the model can limit the number of total plans by assuming that each insurance plan is fully defined by its bin. Individual $i$’s insurance choice in year $y$ can then be described by an indicator function, $I_{iy}$, that is equal to one if she selects insurance plan $j$ and zero otherwise.\textsuperscript{24} This implies that:

$$\sum_{j=0}^{n} I_{iy} = 1 \forall i \forall y$$  \hspace{1cm} (1)

where $j = 0$ defines every individual’s option to decline all plans.\textsuperscript{25 26}

In each period, agents learn of their health status before choosing medical care to maximize utility. There are two types of care that they can consume: doctor office visits and hospital stays. While it would be ideal to model an individual’s decision to consume each of these care types every day over the year (as this is the timing of life), I do not have the data or the computing power to estimate such a model. Therefore, periods are defined as two-month intervals where individuals select how many times they want to visit the doctor, $v_t$, and how many separate hospital stays they will have, $s_t$.\textsuperscript{27} This decision can be represented by a simple indicator function, $d_{it}^{vs}$, that equals one if an individual visits the doctor $v$ times and the hospital $s$ times. If agents can visit the doctor and hospital a maximum of $V$ and $S$ times respectively, then:

$$\sum_{v=0}^{V} \sum_{s=0}^{S} d_{it}^{vs} = 1 \forall i \forall t$$  \hspace{1cm} (2)

now, I combine the two to make one annual deductible. This simplifying assumption may change later, but I’m afraid it may come at a large empirical cost.

\textsuperscript{24} For notational simplicity and consistency, I will include the subscript $i$ to describe individual level variables only when defining the variable. It is up to the reader to remember that these variables describe individuals later in the paper.

\textsuperscript{25} One key difference between this paper and many others modeling insurance decisions is the ability to decline coverage. It is important to allow individuals to decline coverage because (1) a substantial proportion of the population does and (2) take-up is a significant change in one’s consumption pattern that could take place as a result of new policy. Also, with a model of this type it is simple enough to do because the “no plan” option has “plan characteristics” just like any other insurance plan.

\textsuperscript{26} Note also that I presently do not give individuals the option to purchase a private market plan if they deny coverage from their employer. I have this in my data and plan on implementing it into the model eventually.

\textsuperscript{27} Presently, consumers choose hospital “stays” rather than hospital “nights” because most insurance plans that have a co-pay level for hospital care specify the rate by stay and not by night. However, only about 15\% of all plans include a hospital co-pay level, meaning I may be better off disaggregating the “by stay” co-pay level into a “by day” co-pay level so that I am modeling a more realistic decision making process.

\textsuperscript{28} Note that prescription care is not accounted for here. For now, I do not consider this a big problem because prescription drug expenditures generally do not contribute to one’s deductible (need more evidence of this). This means that if it is determined later that they need to be included then it is an easy addition structurally. I have not done it yet because it expands the number of insurance plans, the size of the consumers medical care choice set, and the number of price distributions that they must consider. At this point, I am not sure if such expansions are possible.
3.2 Health Transitions and Probabilities

There are three measures of consumer health that evolve stochastically and endogenously over the year: acute illness state, $A_{it}$; chronic illness state, $C_{it}$; and health stock, $H_{it}$. The first two are learned at the beginning of the period and are binary. Health stock is updated at the end of the period and takes on 1 of 3 values (I only observe one death in my data):

$$A_{it} = \begin{cases} 1 & \text{ill} \\ 0 & \text{well} \end{cases}$$
$$C_{it} = \begin{cases} 1 & \text{ill} \\ 0 & \text{well} \end{cases}$$
$$H_{it+1} = \begin{cases} 1 & \text{poor} \\ 2 & \text{average} \\ 3 & \text{good} \end{cases}$$

First, the probability that an individual contracts an acute illness in period $t$ is written as such:

$$P(A_t = 1) = \pi_t^1 = \frac{\exp(\alpha_0 + \alpha_1 W_t + \alpha_2 H_t + \alpha_3 A_{t-1} + \alpha_4 C_{t-1} + \alpha_5 v_{t-1} + \alpha_6 s_{t-1} + \alpha_7 \text{Int}_A)}{1 + \exp(\alpha_0 + \alpha_1 W_t + \alpha_2 H_t + \alpha_3 A_{t-1} + \alpha_4 C_{t-1} + \alpha_5 v_{t-1} + \alpha_6 s_{t-1} + \alpha_7 \text{Int}_A)}$$

where $\text{Int}_A = (A_{t-1}v_{t-1}, A_{t-1}s_{t-1}, C_{t-1}v_{t-1}, C_{t-1}s_{t-1})$ and $W_t = (\text{sex, race, education, age}).$ The probability of becoming acutely ill is therefore altered by one’s characteristics, overall health (stock), illness status in the previous period, and care consumed in the previous period. Notice that inclusion of the interactions allows for interpretation of $\alpha_5$ and $\alpha_6$ as the effect of preventative care on the probability of getting an acute illness. The interactions also allow $\alpha_3$ ($\alpha_4$) to be interpreted as the marginal effect of having an acute (chronic) illness last period and not consuming care on the probability of acute illness this period. Similarly clear interpretations can be made from coefficients on the interaction terms.

Second, the probability that an individual gets a chronic illness in period $t$ is:

$$P(C_t = 1) = \gamma_t^1 = \begin{cases} \frac{\exp(\delta_0 + \delta_1 W_t + \delta_2 H_t + \delta_3 A_{t-1} + \delta_4 C_{t-1} + \delta_5 v_{t-1} + \delta_7 \text{Int}_C)}{1 + \exp(\delta_0 + \delta_1 W_t + \delta_2 H_t + \delta_3 A_{t-1} + \delta_4 C_{t-1} + \delta_5 v_{t-1} + \delta_7 \text{Int}_C)} & \text{if } C_{t-1} = 0 \\ 1 & \text{if } C_{t-1} = 1 \end{cases}$$

where $\text{Int}_C = (A_{t-1}v_{t-1}, A_{t-1}s_{t-1})$. Thus, $\delta_3, \delta_4,$ and $\delta_5$ can be interpreted similarly to what was explained above, except the marginal effect is now on the probability of chronic illness. Also, notice the assumption that once an individual obtains a chronic disease, it never subsides. This decision was made for several reasons: First, some of the most prevalent chronic illnesses have no cure (e.g. diabetes, asthma, AIDS, etc.). Second, for almost all remaining chronic illnesses, having the disease at some point in life leaves an individual much more susceptible in the future (e.g. cancers, stroke, hypertension, etc.).

---

More interactions will likely be included (here and in all other equations involving interactions), but these are the most important. Feel free to make suggestions.
In these instances, I would argue that the disease is not cured, but is instead being controlled by treatment so that the disease has a lesser negative impact on one’s health. How that idea enters this model will be further explained when the health stock variable is introduced. Third, this is a frequently made assumption in the literature.30

At the end of each period $t$ an individual’s health stock, $H_{t+1}$, is updated before transitioning into the next period. Health stock refers to the long-run health status of an agent. Motivation for the inclusion of a health stock comes from Grossman’s (1972) theory of consumer health care behavior that depicts health as a consumption and production good. Grossman models health as a consumption good because he thought utility was altered by health “flows” and a production good because health is produced by engaging in healthy behaviors. This model takes a similar approach, allowing health stock to enter the utility function and assuming the transition of health stock from period to period is a function of the consumption of medical care.

Health stock transitions are modeled as having the following ordered structure:

$$H_{t+1}^* = v_0 + v_1W_t + v_2H_t + v_3A_t + v_4C_t + v_5v_t + v_6s_t + v_7Int_H + \zeta_{t+1}$$

(5)

$$H_{t+1} = \begin{cases} 
1 & \text{if } H_{t+1}^* \leq 0 \\
2 & \text{if } 0 < H_{t+1}^* \leq \kappa \\
3 & \text{if } \kappa < H_{t+1}^* 
\end{cases}$$

(6)

Where $H_{t+1}^*$ represents latent health stock, $Int_H = (A_t, v_t, s_t, C_{t-v}, C_{t-s})$, and $\kappa$ is a cut-off point to be estimated. Assuming $\zeta_{t+1}$ follows a standard normal logit distribution, the probability of transitioning to each level of health stock is:

$$P(H_{t+1} = 1| \gamma_t) = \eta_{t+1}^1 = \Lambda(-v'Z_t)$$

$$P(H_{t+1} = 2| \gamma_t) = \eta_{t+1}^2 = \Lambda(\kappa - v'Z_t) - \Lambda(-v'Z_t)$$

$$P(H_{t+1} = 3| \gamma_t) = \eta_{t+1}^3 = 1 - \Lambda(\kappa - v'Z_t)$$

(7)

where $v = (v_0, ..., v_7), Z_t = (W_t, H_t, A_t, v_t, s_t, C_{t-v}, C_{t-s})$, and $\Lambda(\cdot)$ is the logistic distribution, which has a closed form. Several features of this function’s design are worth mentioning. First, if a chronic disease

30 (1) To address a past misunderstanding, it is NOT a problem here that most individuals do not learn of their chronic illness until they visit the doctor from the stand-point that it may appear then in the estimates that medical care consumption causes illnesses. Rather, if both medical care is consumed and a chronic illness is realized in the same period, then the model assumes that the chronic illness came first. (2) There is potentially, however, a new problem in that often times people learn of their chronic illness through a series misdiagnosed acute illnesses. This could assign a positive sign to the coefficients on the interaction terms, which is likely incorrect. I will be forced to deal with this problem if it arises.
never goes away then why would anyone ever consume care when they are chronically ill? This equation allows for medical care consumption while in a chronic illness state to alter the impact that the chronic illness state has on one’s health stock (i.e. a diabetic uses an insulin pump to lessen the (likely) negative impact of the disease on their health stock – not to “cure” the disease. The same story could be told for chemotherapy, open heart surgery, or blood-pressure meds.). Second, I include variables for acute illness and medical care while under an acute illness in the equation, though I expect the coefficients on these variable to be zero. That is because these illnesses are seen as short-term episodes that are unrelated to health stock. I include them in this equation, none-the-less, for two reasons: (1) whether or not they impact health stock is an empirical question. (2) Including these terms allow one to interpret \( v_5 \) and \( v_6 \) as the marginal effect of preventative care.

3.3 Utility Function and Budget Constraint

In each period, agents make medical care decisions to maximize the discounted value of their lifetime utility. The period \( t \) utility function (for now) is written as follows:

\[
U(\Psi_t) = \omega'_1 \Delta_t + \omega'_2 A_t + \omega'_3 H_t W_t + \sum_{v=0}^{V} \sum_{s=0}^{S} d_t^{uv} e_t^{uv}
\]

where \( \Delta_t = (1, X_t, H_t, v_t, s_t) \); \( X_t \) represents general consumption, which is determined by the budget constraint discussed below; \( e_t^{uv} \) is the unobserved utility one receives from visiting the doctor \( v \) times and hospital \( s \) times; and \( \Psi_t = \{ W_t, H_t, A_t, C_t, I_{ij}, TE_{yt} \} \) represents the state space, or the set of all information available to an agent at the time of consumption that is relevant to the medical care decision.

There are several features of the utility function that are worth discussing: First, it is assumed that an acute illness does not alter utility directly, but rather alters the marginal effect of general consumption, over-all health, and medical care consumption on utility. In other words, consuming a candy-bar brings less enjoyment when one is acutely ill than it does when well. Second, contrary to Grossman’s theory, health stock and medical care consumption enter the utility function directly. Instead of health stock, Grossman allows the “flow of health” or “healthy days,” which is a function of health stock, to directly impact utility. I am not opposed to this line of thinking and have written the current function as is for simplicity. In the future, I may try to use information in the data (like days gone to work) to measure

---

31 While data limitations will actually prevent me from estimating this as a lifetime utility model, I write the theory as such and amend later for estimation.
32 This utility specification has not been well thought out. Most notably, elements of risk aversion have yet to be introduced. Suggestions here would be greatly appreciated.
33 All variables have been defined except \( TE_{yt} \) which is accumulated out-of-pocket medical care expenditure by individual \( i \), in year \( y \), entering period \( t \). How this value is determined is explained in Section 3.4.
“healthy days” and model this as a function of health stock. Also, Grossman assumes that the demand for medical care is a derived demand, meaning no utility is directly gained through its consumption. Because utility is defined over a much shorter amount of time in this model (2 months vs. 1 year), including medical care consumption is more appropriate because things like travel time, distaste for medical facilities, and psychological effects are much more relevant influencers of choice in the short-run as opposed to the long-run. Third, because it is often found that health status differs for people of different races, educational backgrounds, and ages, personal characteristics and health stock are interacted in the utility function to capture possible differences between these groups in their preferences for health (or tolerance for poor health).

The budget constraint is written as:

\[ X_t = Y_t - P_{jt} - E_t(v_t, s_t, p^1, p^2, I_y, T E_y) \]  \hspace{1cm} (9)

where \( Y_{it} \) is income in period \( t \); \( P_{jt} \) is the period \( t \) premium paid for plan \( j \); \( E_t(\cdot) \) is expenditure on medical care in period \( t \); and \( p^1_t \) and \( p^2_t \) represent the total price of a doctor’s office visit and a hospital stay respectively. There are two features of medical care markets that make determining this expenditure very interesting. First, because of health insurance, individuals often-times do not pay the total price of medical care. Rather, they pay an out-of-pocket price that is a function of the total price, insurance plan characteristics, and annual expenditure entering period \( t \). Second, the total price of medical care is often unknown at the time of consumption. This is due to both lacking of menu prices and the uncertainty of diagnosis. Because the total price for care is unknown at the time of consumption, the out-of-pocket price, which is a function of the total price, is (often) unknown as well. In light of these complications, the next section is dedicated to explaining how individuals will regard the price of medical care in this model.

3.4 Medical Care Expenditures:

The decision of how much medical care to consume within a period is based, at least partially, on the expenditure required. Assuming momentarily that total prices are known at the time of consumption, one can determine out-of-pocket expenditure in a period with \( v_t \) doctor’s office visits and \( s_t \) hospital stays using equations A1 and A2 (found in Appendix 1). Total out-of-pocket (OOP) expenditure, \( E_t \), is then determined by adding OOP doctor’s office expenditure, \( e_{it}^1 \), and OOP hospital expenditure, \( e_{it}^2 \), which are each written as functions of the total prices for care, the number of trips to each care facility, expenditure
entering the period, and characteristics of the insurance plan. The OOP expenditure equation and the accumulation of total expenditure entering each period, $TE_{iyt}$, can be seen below.

$$E_t(v_t, s_t, p^1, p^2, I^1, TE_{yt}) = e^1_t + e^2_t$$

$$TE_t = \begin{cases} TE_{t-1} + E_{t-1} & \text{if } t > 1 \\ 0 & \text{if } t = 1 \end{cases}$$

Figure 2 helps one understand how equations A1 and A2 work. Insurance alters consumer behavior by creating non-linearities in the price of medical care. Specifically, the proportion of the total price that one must pay out-of-pocket depends on (1) whether or not one’s deductible has been reached, (2) whether or not one’s MOX has been reached, and (3) the co-insurance rate and/or co-pay level of one’s plan. The six lines in Figure 2 correspond to the six levels in each out-of-pocket expenditure function and represent all possible relationships between total expenditure, one’s deductible, and one’s MOX. At each level, the proportion of the total price that a consumer is required to pay changes. At the first level, the consumer begins and ends the period without passing the deductible; thus she pays the total price for each unit of care. At the second level, the consumer begins the period below the deductible but passes it during the period. In this situation, she is responsible for paying the full price of care for each visit before the deductible is reached and a fraction of the price after the deductible has been passed. This fraction is determined by the co-insurance rate and/or co-pay level specified by her insurance plan. At the third level, the agent begins the period not having passed the deductible and consumes enough care within the period that she not only surpassed the deductible but reaches the MOX as well. In this case, she pays the total price for visits prior to the deductible, a fraction of the price for visits between the deductible and MOX, and nothing for visits after her total expenditure has passed the MOX level. The remaining three levels specify cases in which the agent begins the period with expenditure between the deductible and MOX and doesn’t pass the MOX, between the deductible and MOX and passes the MOX, and past the MOX.

Two necessary assumptions are implicit in equations A1 and A2. First, this specification assumes that the total prices charged for a doctor’s office visit and for a hospital stay are fixed for individual $i$ within any period. In other words, I assume that the total price that individual $i$ is “charged” for a general check-up in period $t$ must be the same as the total price charged for a flu treatment for the same individual in the same period (assuming both are done in a doctor’s office). This assumption makes the problem empirically tractable. As will be seen momentarily, the agent solves their optimization problem by integrating over

34 Note that the OOP expenditure on each of these two types of medical care must be determined separately because many insurance plans specify separate co-insurance rates and co-pay levels for doctor’s office and hospital care.

35 It is important for the reader to understand that some plans will have a co-pay AND co-insurance rate for doctor/hospital care. Thus, I assume in these equations that co-pay is always paid first and co-insurance is paid on the remainder.
two distributions of possible prices. If this price were allowed to vary for each trip to the doctor/hospital in a period, then a $V \times S$ dimensional integral would need to be solved in every period. Further, given that the factors influencing the total prices one faces within a period are not changing, it seems reasonable to assume that this total price doesn’t change. Second, the equation assumes that all doctor’s office visits are made before any hospital visits take place. While this assumption is clearly not ideal, it is necessary if one hopes to avoid modeling the specific order in which agents decide to visit the doctor and hospital, which would cause the size of the alternative set to explode.  

While this set of equations provides a relatively clean way to calculate the period $t$ expenditure, $E_t$, that enters the budget constraint, the assumption that agents know the total price of medical care at the time of consumption is not realistic. A more reasonable supposition is that each total price is drawn from a distribution conditional on one’s personal and health characteristics and that the individual is able to form expectations over this distribution when solving their optimization problem. As such, I define $F(p^1|\Gamma_t; \beta_1)$ and $G(p^2|\Gamma_t; \beta_2)$ to be conditional distributions determining the period $t$ total price for a doctor’s visit and hospital stay respectively, where $\Gamma_t = \{W_t, H_t, A_t, C_t, N_j, I_1\}$.  

3.5 The Optimal Per-Period Decision Rule

In this section, I derive a function to represent an agent’s discounted lifetime utility in any period $t$. The function is written conditional on a chosen insurance plan; therefore, it can be discounted back to the $t = 0$ time period, where it can be used to represent the expected future benefit of a plan at the beginning of the insurance year. This value and a plan specific error term will be used to model individual insurance decisions.

To begin, I define the value of discounted lifetime expected utility in period $t$, following medical care consumption decision $d^{cs}_t$, conditional on insurance plan $j$ and treatment prices $p^1$ and $p^2$ for two situations; when $t = T$ and $t < T$.

---

36 Note that order is important because it determines when exactly during the period the deductible or MOX is passed. If people are uncomfortable with this assumption, consider the two alternatives: (1) I could force agents to select not only the number of visits but the order as well. This is likely empirically infeasible. (2) I could stipulate that non-linear changes in medical care prices that happen when one crosses the deductible or MOX only occur between periods. This would greatly simplify the budget constraint; however, it would remove important variation from the data.

37 Two of these determinants may need further explanation for some. $N_j$ is included due to the fact that HMOs often times do not have traditional cost-sharing features like deductibles and co-pay. Rather, these plans simply limit individuals to a network of doctors who have agreed to charge a reduced-total price to anyone having insurance from in the HMO. Also, the indicator for no insurance is included because most insurance carriers have agreements with a medical care providers that discount total prices even before cost-sharing features are applied.
For $t < T$:

$$
V_{vs}(\Psi_t, \epsilon_t^{vs}|p^1, p^2, l^j_y) = \bar{U}_{vs}(\Psi_t) + \epsilon_t^{vs} + \beta \sum_{n=1}^{3} \eta_{t+1}^{n'}(\Psi_t, v_t, s_t) \left[ \sum_{\pi = 0}^{1} \pi_{t+1}^{n}(\cdot, H_{t+1}) \sum_{\eta = 0}^{1} \gamma_{t+1}^{n}(\cdot, H_{t+1}) [V(\Psi_{t+1}|l^j_y)] \right]
$$

(12)

For $t = T$:

$$
V_{vs}(\Psi_t, \epsilon_t^{vs}|p^1, p^2, l^j_y) = \bar{U}_{vs}(\Psi_t) + \epsilon_t^{vs} + \beta \sum_{n=1}^{3} \eta_{t+1}^{n'}(\Psi_t, v_t, s_t)[Q_{y+1}(\Psi_0, H_1)]
$$

(13)

where $\bar{U}(\cdot)$ is the deterministic part of equation (8) and $Q_{y+1}(\Psi_0, H_1)$ is the discounted value of lifetime expected utility in period $t = 0$ of year $y + 1$.\(^{38}\) After this, the value function can be written unconditional on the price distribution as:

$$
V_{vs}(\Psi_t, \epsilon_t^{vs}|l^j_y) = \int_0^\infty \int_0^\infty f(p^1|\Gamma_t) g(p^2|\Gamma_t) * V_{vs}(\Psi_t, \epsilon_t^{vs}|p^1, p^2, l^j_y) d(p^1) d(p^2)
$$

(14)

where $f(\cdot)$ and $g(\cdot)$ are the conditional density functions from which $p^1$ and $p^2$ are drawn.\(^{39}\) Because $V_{vs}(\Psi_t, \epsilon_t^{vs}|l^j_y)$ represents the entire discounted lifetime value of decision $k$ at time $t$ for every $t$, I can form the following optimal decision rule:

$$
V(\Psi_t|l^j_y) = E_{t-1}\left[ \max_{\epsilon_t^{vs}} V_{vs}(\Psi_t, \epsilon_t^{vs}|l^j_y) \right]
$$

(15)

### 3.6 The Optimal Annual Decision Rule

Using the period 1 value function and the timing assumptions of the model, I can represent the time 0 value function (before period 1 illness states are known) as follows:

$$
V(\Psi_0, H_1|l^j_y) = \sum_{n=0}^{1} \pi_1^{n'}(\cdot, H_1) \sum_{\eta = 0}^{1} \gamma_1^{n}(\cdot, H_1) [V(\Psi_1|l^j_y)]
$$

(16)

---

\(^{38}\) I do not have the data to estimate this as is. I only observed one insurance decision, meaning I cannot look at lifetime utility. As such, rather than selecting medical care consumption in the last period of the year to maximize lifetime utility, I will create a closing objective function to replace $Q_{y+1}$. This closing function will approximate the discounted expected utility gained over the rest of one’s lifetime.

\(^{39}\) Note that this amounts to the consumer calculating the value of each decision under every price combination in the support of the price distributions, then assigning weight to each of these valued according to how likely each price combination is.
In other words, this is the discounted future expected utility that an agent would gain over their lifetime from insurance plan $j$ in insurance year $y$. Theoretically, this value should be a very important aspect of one’s insurance decision. Because this value has been computed for every $j$, I can represent the total utility that one gains from plan $j$ as a function of the following variables:

$$ Q_y^j(\Psi_0, H_1, \phi_y^j) = f(V(\Psi_0, H_1; l_y^j), N_j, \phi_y^j; \theta) $$

(17)

where $N_j$ is included to allow people to simply prefer HMOs, PPOs, or open style plans. The last term is unobserved utility individual $i$ gets from plan $j$.

Again, I can form a decision rule on this value function such that:

$$ Q_y(\Psi_0, H_1) = \mathbb{E}_{y-1}[\max_j Q_y^j(\Psi_0, H_1, \phi_y^j)] $$

(18)

## 4 Data

### 4.1 Description of the Survey

As discussed earlier, the biggest difficulty in estimating the above model is finding a data set that provides sufficient information. I will argue that, after making a few reasonable assumptions, the 1996-1999 Medical Expenditure Panel Survey (MEPS) provides enough information to estimate this model.\(^{40}\) I will explain the details of each file that I use in estimation.

The primary data file in the MEPS collection is the Household Component (HC). This file contains health status, employment, and demographic information for a nationally representative sample of the U.S. civilian non-institutionalized population. Survey participants are randomly drawn from individuals responding to the previous year’s National Health Interview Survey. The data collection process is described as having an overlapping panel design. Specifically, a new survey cohort has begun every year from 1996 to the present. Individuals in each cohort are interviewed 5 times over the 2 years that follow January 1st of their cohort year. Thus, the term “overlapping panel design” is derived from the fact that each person is interviewed multiple times and, in every year but the first, individuals from two different cohorts are interviewed.

\(^{40}\) The MEPS data are collected by the Agency for Healthcare Research and Quality (AHRQ). More information can be gathered at [http://www.meps.ahrq.gov/mepsweb/](http://www.meps.ahrq.gov/mepsweb/).
The second file used in the construction of my data was the MEPS Insurance Component (IC). The IC is an annual survey of employers that reports insurance offerings, plan characteristics, and employer characteristics for two samples of employers. The IC list sample, which I do not use, is a nationally representative sample of private and public employers. The IC household sample, which I do use, is made up of employers whose have an employee participating in the HC. Thus, AHRQ uses information provided in the first round of the HC survey to identify an individual’s specific employer. Then employers are contacted and questioned about their firm’s characteristics and the insurance they offer to their employees. A “Link” file is then formed by matching employee information in the HC to employer responses in the IC household sample to provide a complete picture of the employee’s health insurance choice set and his or her insurance decisions. While the formation of this Link file is the primary feature that sets this data file apart from others, its formation is also the cause of three significant problems. First, AHRQ only attempted to collect the IC household sample from 1996-1999 and again in 2001. Thus, the Link file could only be formed for five years. Second, employers were contacted twice (once at the beginning of each year) for only a very small number of individuals in the HC. Therefore, only a model with one insurance decision can be estimated using these data. Third, many individuals refuse to give their employers information so that they can be contacted and many employers refuse to participate in the survey, despite their employees inclusion in the HC. As a result a significant proportion of the nationally representative HC participants (roughly half) are not linked to any insurance information in the IC file. A general idea of the non-representativeness problem that may arise from this can be seen in Table 2.

The final two files that I use in estimation are the Medical Conditions file (MC) and the Medical Expenditure files (ME). The MC file was collected directly from each individual included in the HC file. Interviewers recorded detailed descriptions of each illness episode obtained in or experienced during a survey period. Later, professionally trained coders imputed an ICD-9 condition code for each illness reported. For sicknesses deemed “priority conditions” (mostly popular chronic conditions) by survey designers, more detail was gathered about the illness. Most importantly, this information included the date that the priority condition began. The ME files contain a set of smaller files detailing all doctor office, hospital in-patient, hospital out-patient, dental, and emergency room visits, as well as prescription drug

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41 There was one significant change to the IC collection process that took place after 1996. The 1996 IC asked each employer specific questions regarding their employee in the HC sample. This method caused many employees to be resistant in providing their employers information as employees wished to remain anonymous. The method also troubled 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, from 1997-1999, the collection process was altered such that employers were only asked general information about their insurance offerings. AHRQ then used a complex matching procedure to identify which offered plan was reportedly chosen by employees in the HC.

42 The 2001 information does not include in it the month that a plan’s insurance year began. Because of this missing information, I am unable to use data from this year.
consumption. Individuals and their medical care providers are questioned about each visit to uncover information on the visit date, the service provided, the out-of-pocket and total cost, etc.

4.2 Determination of the sample

The population of study is selected from the nationally representative sample of individuals included in the 1996-1999 cohorts of the MEPS HC survey. Right now, I am considering three different possible samples. All three groups are composed of continuously employed individuals between the ages of 19 and 64 whose employers offer them subsidized health insurance. The samples are restricted by age to avoid the unique decision making process of children with possible access to their parents health insurance plans and the elderly, who have access to plans offered through Medicare. The unemployed and employed without an insurance offer are excluded because no insurance information was gathered for these individuals. Additionally, individuals in all three samples must have the same insurance status for the entire year, meaning they are either always uninsured or insured by the same plan.

The three samples are further restricted to only include individuals whose employer subsidized insurance plans are contained in the Link file described above. This is required to model individuals’ insurance decisions. The samples also exclude all individuals taking-up plans for which the insurance year does not begin in January. This must be done because insurance information is only gathered in an individual’s round 1 interview, which always takes place in January, February, or March of their cohort year. Anyone possessing a non-January plan then has likely consumed care prior to the time covered by the first interview period (January 1st – interview date). Consumption before January 1st is problematic in estimation because the agent does not enter the year with $T_{E_yt} = 0$.

Of the individuals that qualify under these restrictions, three samples are created, which can be seen in Table 1. The first sample contains only single individuals with no children. If it were not for the small number of observations, this sample would be the most preferred as all individuals choose only from single coverage plans. Because this sample only contains 887 individuals I am willing to include other individuals at the risk of losing some generalizability of the results. The second sample includes all people in the first sample who do not have kids, do not hold a family plan, and are not covered by their spouse’s family plan. The reason for omitting people with children is that adults without children likely share more common traits and lifestyles with single people that do parents. The third sample is just like

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43 I also drop full time students under the age of 24 because federal law allows these individuals to stay on their parents insurance plan.
44 Modeling the choices of individuals with family plans in this framework is very difficult because family plans are chosen with all covered individuals in mind. In this model, that would require discounting the value of a plan and future medical care choices for every member of the family…no thanks.
the second except people with children are not omitted (referred to as “All Inclusive”). There is one problem that cannot be fixed in the latter two samples. It is that, while I can see whether or not individuals are covered by and/or hold an outside option, I cannot see whether or not a held outside option is a single or family plan. As such, when I do work the outside option into the model, these samples will cause slight problems.\footnote{However, very few individuals take-up an out-side insurance option. So the issue is not too problematic.}

There are a few irregularities in Table 1. First, in all samples, there is a disproportionate large drop when individuals not included in the Link File are excluded from the sample in 1996 and 1998. In 1996, this was likely due to the fact that interviewers asked employers about exact employees in the interview and many refused (see footnote 40). In 1998, interviewers only attempted to collect insurance information for 25\% of the sample. Second, the percentage lost at the “take-up and plan type consistent” step is much large for the third sample than the other two. This is because individuals taking-up family plans are removed in this step. Third, there are question marks for individuals in the 2001 sample in certain cells because employers were not asked what month the plan started in by interviewers in 2001. These data may not be used then.

4.3 Sample Statistics and Basic Correlations:

Tables 2 – 5 offer sample statistics and some basic correlation findings to support the potential existence of moral hazard and adverse selection.\footnote{Evidence of KNPs result cannot yet be given because within period data has yet to be cleaned.} Table 2 compares the personal and health variable means of a “representative” group of continuously employed individuals between the ages of 19 and 64 that get an insurance offer from their employer, with the single and all inclusive samples. This table is included to give the reader an idea of how representative the data are after being restricted for inclusion in the link file, January plans, and single coverage only. The two samples seem relatively similar except the estimation samples have significantly more federal employees, which is expected because insurance information can be collected without interviewing the employer. Also, the estimation files have significantly more females. I have not yet thought of a story for why this may be the case.

Table 3 shows the difference between individuals taking and declining employer provided insurance.\footnote{At this point, some of the individuals included in the decline column actually take-up insurance in the open market.} Individuals with insurance are more likely to be older, more educated, female, white, federal employees, and white collar. Those with insurance are also significantly richer and spend much more on medical care than those declining.
Table 4 compares plans that are taken up with those that are declined. It is easy to see that consumers are highly motivated by out-of-pocket premiums. One will also notice that deductible and co-pay levels tend to be lower (more generous) for declined plans. I apologize for not having co-insurance information included here. I screwed up the code and didn’t recognize it until it was too late to return to the Census lab. Also, the highlighted cell is unsuspectingly large because I did not notice an outlier.

Tables 5 and 6 show correlations between total premiums (a proxy for plan generosity), expenditure, and health for the single and all-inclusive samples. The premium and expenditure are positively correlated suggesting presence of adverse selection or moral hazard. Unfortunately, correlation between total premium and early health, which would be further evidence of adverse selection, is zero. Correlation between health and expenditure is positive early in the year and late, suggesting that less healthy people are buying more care. Not included in the graphs are negative correlations between deductible and expenditure in each sample.

5 Empirical Strategy

There are six critical issues in estimating the model that I have identified thus far: (1) the distribution over true medical care prices (CDE), (2) controlling for unobserved heterogeneity (DMF), (3) missing information (integrating over the likelihood function), (4) using interpolation methods to allow for continuous variables in the state space, (5) construction of a likelihood function, and (6) the estimation procedure. I will explain what I understand at the moment. This part of the project (and cleaning the rest of the data) is where I have the most work to do…

5.1 Conditional Density Estimation of the Price distributions

Typically, when integrating a variable out of the value function, as is done here with prices, the econometrician must assume a distribution. For example, in this paper a reasonable assumption may be that prices are normally distributed, wherein one could integrate over the two distributions using simulation techniques. Another feasible solution would be to assume that prices come from a discrete distribution where \( k \) points of support are chosen; then, rather than integrating over the distributions the value function is computed for every possible price and weighted by the estimated probability of each price in the likelihood function. Unfortunately, there are two problems with these types of estimation strategies. First, there is no reason to suspect that either the total price of a doctor's office visit or a hospital stay comes from a traditional distribution (such as normal, log-normal, or discrete). One could even argue that the evidence would point to these prices coming most likely from a non-traditional distribution. (Given that hospitals offer preventative care, such as mammograms, as well as chronic care,
such as triple by-pass surgery, there is reason to believe that the distribution over these prices could even be bi- or tri-modal.) As a result, improper specification of this distribution is likely, which would lead to bias using MLE. Second, in most techniques that assume a distribution, parameters are estimated by trying to explain the first moment of the outcome distribution (OLS for example attempts to explain the mean outcome). However, in a market like medical care where excessive expenditure is an important policy issue, capturing the tails of the price distribution may be equally important.

Because of these known drawbacks to assuming a distribution over prices, I hope to use a lesser practiced technique called Conditional Density Estimation (CDE) in estimating the model. Initially described by Gilleskie and Mroz (2004), CDE “uses a sequence of conditional probability functions, similar to those used in discrete time hazard rate analysis, to construct a discrete approximation to the density function of an outcome of interest conditional on exogenous covariates.” Understanding is easily gained through the following example: Assume \( f(y|x) \) describes the unknown conditional density of outcome variable \( y \) and independent variables \( x \). For some discretization of the support of \( y \), an individual could represent the probability that \( y \) fell in the \( k^{th} \) interval \([y_{k-1}, y_k)\) conditional on not having fallen into one of the previous \( k - 1 \) intervals by:

\[
\lambda(k, x) = \text{Prob}[y_{k-1} \leq Y < y_k | x, Y \geq y_{k-1}] = \frac{\int_{y_{k-1}}^{y_k} f(y|x)dy}{1 - \int_0^{y_{k-1}} f(y|x)dy} \tag{19}
\]

According to hazard function properties, the probability that \( y \) falls into interval \( k \) can then be written as:

\[
\text{Prob}[y_{k-1} \leq Y < y_k | x] = \lambda(k, x) \prod_{j=1}^{k-1} [1 - \lambda(j, x)] \tag{20}
\]

Then, for any function of the outcome variable \( h(y) \) an approximation of the expectation of the function conditional on \( x \) can be written as:

\[
\bar{E}[h(y)|x] = \sum_{k=1}^{K} h^*(k|K)\lambda(k, x) \prod_{j=1}^{k-1} [1 - \lambda(j, x)] \tag{21}
\]

where \( h^*(k|K) \) is some previously specified approximation to \( h(y) \) in the \( k^{th} \) interval of the outcome support (most-often it is simply the average of \( h(y) \) over the support).

Without a distributional assumption for \( f(\cdot) \) this expectation cannot be approximated. However, according to Heckman and Singer (1984) the presence of unobserved heterogeneity can break down the
conditional independence implicit in equation (21) if the distributional specification is incorrect. Therefore, Gilleskie and Mroz (2004) avoid the distributional assumption by using a sequence of conditional logit functions to approximate the $K$ hazard rates. Using advanced methodology in selecting the number of intervals $K$, the size of each interval $[y_{k-1}, y_k)$, and an extensive, empirically contrived set of polynomials in functions of the covariates, they are able to show using Monte Carlo simulation that estimates derived using their single logit sequence approximation to the hazard rate out-performed more common estimation techniques with typical distributional assumptions. Additionally, because the entire outcome distribution was estimated, the marginal effects of covariates could vary smoothly over the outcome distribution. With regard to price distributions in this paper, this feature of CDE is attractive because medical conditions, like a chronic disease, may have a very different impact at the top and bottom of the price distribution.

Given the obvious advantages, I hope to implement the CDE technique into my estimation procedure. I will use the technique derived by Gilleskie and Mroz to select $K_1$ intervals in the doctor’s office price distribution and $K_2$ intervals in the hospital price distribution. I also use their technique in selecting the size of interval and number of polynomials. Then, the previous equation (14) can be re-written such that:

$$V_{wS}(\Psi_t, \epsilon_t^{wS} | I_y) = \sum_{k=1}^{K_1} \sum_{k'=1}^{K_2} \lambda_t^{1k'} \lambda_t^{2k''} V_{wS}(\Psi_t, \epsilon_t^{wS} | p^1, p^2, I_y)$$

(22)

where

$$\lambda_t^{qk} = \text{Prob}[p_{k-1}^q \leq p^q < p_k^q | x] = \lambda^q(k, x) \prod_{j=1}^{k-1} [1 - \lambda^q(j, x)] \equiv \frac{\exp(x_k \beta^q)}{1 + \exp(x_k \beta^q)}$$

(23)

where the last equivalence sign is to be interpreted as “will be approximated by.” In other words, I will approximate each hazard rate by one logit probability (for each medical care type), where the probability of falling into each interval varies only because the independent variables included in each probability are different (polynomials in functions of covariates and the interval number).

5.2 Unobserved Heterogeneity:

The trade-off one faces when using MLE is small standard errors for strict assumptions about the unobservable parts of the model. In this work, these come in the form of assumptions about the distribution of unobservable factors in equations (3), (4), (5), (8), (17), and the total price distributions – and – the assumed independence of these unobserved factors. Rosenzweig and Schultz (1983) discuss
why the latter of these is a very big problem in models of health inputs and outcomes. With regard to this paper, notice that I do not have any measure for one’s attitude about health. However, individuals who value health are more likely to partake in all health activities, including more medical care consumption when sick, better eating habits, more exercise, etc. Thus, one’s attitude about health is likely found in the error term of the health equations and per-period utility equation, meaning they are not independent.

Allowing for correlation between unobservables is also important for estimating adverse selection and moral hazard. It is assumed that there are unobserved factors that influence both one’s insurance choice and their consumption of medical care during the year. For example, someone expecting a chronic disease (like a life-long smoker) should be more likely to buy generous insurance (because they expect the onset of the disease) and should consume more care (given the onset of the disease). Therefore, to identify the impact that the insurance plan has on behavior (moral hazard) separately from selection into the plan based on expected behavior (adverse selection), unobserved correlation between the decisions must be controlled for.

One way to allow for this dependence in unobservables is to assume a joint distribution and allow for correlation, but this requires rigid distributional assumptions and puts restrictions on the timing of the model. A better alternative is using a discrete factor random effects approach (DFM). This method allows the unobserved heterogeneity components of each equation to be approximated by a discrete step-wise function (see Heckman and Singer, 1984; Mroz and Guilkey, 1992; and Mroz, 1999). Using Monte Carlo simulations, Mroz (1999) was able to show that when the true error distribution was joint normal, the discrete factor method estimates compared favorably to those derived using the correct distribution. However, when the true error distribution was not normal, the discrete factor method outperformed all other estimation methods.

To give an overly simplified description of DFM, each disturbance term in the model is rewritten as:

\[ \chi_{aiz} = \rho_{az} \mu + u_{aiz} \]  \hspace{1cm} (24)

where \( \chi_{aiz} \) represents the error term from equation \( a \) for individual \( i \) associated with alternative/outcome \( z \). The “discrete factor” is represented by \( \mu \). This term approximates an unobserved factor that affects all transition probabilities and choices of individual \( i \). It is assumed that the factor follows a discrete distribution with finite support, where the number of points of support is chosen by the econometrician. Thus, an individual’s estimated factor value can be thought of as an unobserved “type” influencing all of the models decisions and outcomes. The factor loading term, \( \rho_{az} \), captures the influence that the factor
has on the outcome/choice in equation \(a\). The final term \(v_{ait}\) is the remainder of the error term. To estimate, I am forced to make assumptions about the distribution of these disturbances.

5.3 *Missing information:*

Donna and I have discussed integrating over the likelihood function to control for the missing elements in estimation (initial conditions and missing health stock variables every other period). I have not yet had time to really consider what this entails.

5.4 *Using Interpolation Methods to Allow for Continuous Variable in the State Space*

I have some continuous stuff in the state space and may eventually have more. I know “interpolation” has something to do with continuous state variables…but I literally know nothing more than that.

5.5 *Likelihood Function:*

I cannot do this until I have figured the above 4 things out

5.6 *Estimation Procedure:*

Presently, I understand how the estimation technique would work if (1) CDE were not used (if I assumed prices were just determined by a multinomial logit structure), (2) I wasn’t modeling individual heterogeneity, (3) there was no missing information, and (4) all elements in the state space were discrete.

6 *Bibliography*


Appendix 1

Figure 1:

From Keeler, Newhouse, and Phelps (1977): page 646, Figure 2.

Figure 2:
Equation A1: Out-of-pocket expenditure in doctor’s office care:
\[ e_t^1(v_t, p_t^1, \Psi_t) = \begin{cases} p_t^1 * v_t & \text{if } p_t^1 * v_t \leq r_t^1 < z_t^1 \\ r_t^1 + \int \frac{p_t^1 * v_t - r_t^1}{p_t^1} * C_j^{d2} + \max \left\{ 0, p_t^1 * v_t - r_t^1 - \int \frac{p_t^1 * v_t - r_t^1}{p_t^1} * C_j^{d1} \right\} * C_j^{d1} & \text{if } 0 < r_t^1 < p_t^1 * v_t < z_t^1 \\ r_t^1 + \int \frac{z_t^1 - r_t^1}{p_t^1} * C_j^{d2} + \max \left\{ 0, z_t^1 - r_t^1 - \int \frac{z_t^1 - r_t^1}{p_t^1} * C_j^{d2} \right\} * C_j^{d1} & \text{if } 0 < r_t^1 < z_t^1 \leq p_t^1 * v_t \\ v_t * C_j^{d2} + v_t * (p_t^1 - C_j^{d2}) * C_j^{d1} & \text{if } r_t^1 = 0 \text{ and } p_t^1 * v_t \leq z_t^1 \\ \int \frac{z_t^1}{p_t^1} * C_j^{d2} + \left( z_t^1 - \int \frac{z_t^1}{p_t^1} * C_j^{d2} \right) * C_j^{d1} & \text{if } r_t^1 = 0 \text{ and } 0 < z_t^1 < p_t^1 * v_t \\ 0 & \text{if } r_t^1 = 0 \text{ and } z_t^1 = 0 \end{cases} \]

where \( r_t^1 \) = The amount remaining in one’s deductible = max\{0, D_j^1 - TE_t\}
\( z_t^1 \) = The amount remaining in one’s MOX = max\{0, D_j^2 - TE_t\}

Equation A2: Out-of-pocket expenditure on hospital care:
\[ e_t^2(s_t, p_t^2, e_t^1, \Psi_t) = \begin{cases} p_t^2 * s_t & \text{if } p_t^2 * s_t \leq r_t^2 < z_t^2 \\ r_t^2 + \int \frac{p_t^2 * s_t - r_t^2}{p_t^2} * C_j^{h2} + \max \left\{ 0, p_t^2 * s_t - r_t^2 - \int \frac{p_t^2 * s_t - r_t^2}{p_t^2} * C_j^{h1} \right\} * C_j^{h1} & \text{if } 0 < r_t^2 < p_t^2 * s_t < z_t^2 \\ r_t^2 + \int \frac{z_t^2 - r_t^2}{p_t^2} * C_j^{h2} + \max \left\{ 0, z_t^2 - r_t^2 - \int \frac{z_t^2 - r_t^2}{p_t^2} * C_j^{h2} \right\} * C_j^{h1} & \text{if } 0 < r_t^2 < z_t^2 \leq p_t^2 * s_t \\ s_t * C_j^{h2} + s_t * (p_t^2 - C_j^{h2}) * C_j^{h1} & \text{if } r_t^2 = 0 \text{ and } p_t^2 * s_t \leq z_t^2 \\ \int \frac{z_t^2}{p_t^2} * C_j^{h2} + \left( z_t^2 - \int \frac{z_t^2}{p_t^2} * C_j^{h2} \right) * C_j^{h1} & \text{if } r_t^2 = 0 \text{ and } 0 < z_t^2 < p_t^2 * s_t \\ 0 & \text{if } r_t^2 = 0 \text{ and } z_t^2 = 0 \end{cases} \]

where \( r_t^2 \) = The amount remaining in one’s deductible = max\{0, D_j^1 - TE_t - e_t^1\}
\( z_t^1 \) = The amount remaining in one’s MOX = max\{0, D_j^2 - TE_t - e_t^1\}
### Appendix 2

#### TABLE 1: Sample Selection Information

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TABLE 2: Representative vs. Estimation Sample

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### TABLE 4: Features of Taken and Declined plans

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### TABLE 5: Correlation Between Key Healthcare Variables (Single)

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### TABLE 6: Correlation Between Key Healthcare Variables (All Inclusive)

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