Reference dependent utility from health and the demand for medical care

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Abstract

We examine the effect of reference health on the demand for medical care. We propose and empirically implement a dynamic model of demand for medical care that includes reference health, an average of previous health states. We find that gain or loss from reference health significantly affects the demand for medical care. The effect is stronger for losses than gains. The effect is strongest in the upper tail of medical care consumers. We compare the predictions of our dynamic model with one that omits reference health. Including reference health improves our ability to match individuals in the top 5 percent by 65 percent.

Keywords: Reference Dependence, Human Capital, Demand for Medical Care, Health Dynamics, Semi-Parametric, Conditional Density Estimation

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I Introduction

This paper incorporates elements from prospect theory in a dynamic model of demand for medical care, allowing utility from health to be reference-dependent with respect to health in previous periods (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991; Koszegi and Rabin, 2006, 2009; Baucells et al., 2011). The incorporation of reference health in the utility function enables us to better explain why some relatively healthy individuals consume high levels of medical care, and why some individuals in poor health do not. Existing economic models of health capital and medical care demand specify utility only as a function of contemporaneous health and consumption and have difficulty explaining the observed distribution of medical care spending (Grossman, 1972; Ehrlich and Chuma, 1990; Galama, 2011).

In the United States, medical care expenditures account for 17.7 percent of Gross Domestic Product (GDP), and nearly nine percent of GDP (half of all expenditures) is spent by the top five percent of medical care consumers (World Bank, 2014; Claxton et al., 2014). Thus, understanding the demand for medical care at the top end of the spending distribution is more important than explaining the behavior of the mean or median consumer, whether predicting changes in expenditures, managing financial risk, informing physician or facility capacity decisions. However, not all high medical care spenders are in poor health. In fact, fewer than 20 percent of the top 5 percent of spenders report poor health, while 7.5 percent report excellent health (Schoenman, 2012). Similarly, not everyone in poor health is a high consumer of medical care. Nearly 40 percent of medical care spending by individuals in poor health is incurred by the top 5 percent of that group (Claxton et al., 2014).

First, we present a simple two-period model to illustrate why individuals experiencing a decline from reference health will demand more medical care, independent of their current state of health.[1] By comparing and contrasting our equilibrium conditions with

[1] Our model is a simplification of the continuous time optimal control model presented in Kohn and Patrick (2012).

existing models that do not include reference health, we show why including reference health can better explain the top tail of the medical care spending distribution.

Next, we empirically evaluate our model by nesting a joint semi-parametric conditional density estimation of the demand for medical care, consumption, and the evolution of health in a finite mixture framework. Using the RAND Health and Retirement Survey Data (HRS), we find that an individual's reference health significantly affects her demand for medical care. While reference health affects the demand for medical care at all levels of spending, the effect is strongest at the top of the distribution of medical spending. An individual whose contemporaneous health is 10 percent lower than her reference health is 22 percent more likely to be in the top 5 percent of medical care consumers (consuming over $10,000 per year) than an individual with the same contemporaneous health who did not experience a decline from reference health. We also compare the predictions of our dynamic model with one more consistent with the extant literature (omitting reference health). Including reference health improves our ability to match individuals in the top 5 percent by 65 percent. Thus, while poor health matters, we show that modeling the path to poor health better enables us to predict which individuals end up in that top 5 percent. This is policy relevant as these individuals account for 50 percent of all medical care expenditures.

Principally, this paper is the first to our knowledge to intersect the prospect theory and reference-dependence literature with the human capital and health demand literature(Kahneman and Tversky, 1979; Tversky and Kahneman, 1991; Koszegi and Rabin, 2006, 2009; Grossman, 1972; Ehrlich and Chuma, 1990; Galama, 2011). By incorporating reference dependence in the utility function, we extend the literature that models the effects of reference dependent preferences on health, including rational addiction (Becker and Murphy, 1988). As our reference point is formed using adaptive expectations, we extend the literature on adaptation to changes in health states (Groot, 2000; Contoyannis et al., 2004) and wealth states (Constantinides, 1990).

We also contribute to other recent theoretical and empirical work in dynamic models of heath and wealth over the lifecycle by focusing on explaining high medical care spending. This other work (Hall and Jones, 2007; Edwards, 2008; Yang et al., 2009; Yogo, 2009; Khwaja, 2010; Hugonnier et al., 2013; Monahan, 2013) has focused on explaining consumption and investment decisions modeling health care expenses as only one input to those decisions. Whereas prior work has focused on the conditional mean, we focus on explaining the upper tail of medical care consumers.

Additionally, we offer empirical evidence on the relationship between health and utility from consumption that can help reconcile conflicting findings in the literature (Edwards, 2008; Finkelstein et al., 2009). Finally, we contribute to the literature on empirically modeling skewed distributions of medical care by nesting a semi-parametric joint estimation of conditional densities within a finite mixture framework (Cameron and Trivedi, 1986; Pohlmeier and Uhlrich, 1995; Cameron and Johansson, 1997; Deb and Trivedi, 1997; Gurmu, 1997; Shen, 2013).

The rest of the paper proceeds as follows: Section II presents a simple two-period economic model that highlights the role of reference dependent utility from health in explaining high medical care demand. Section III details our estimation strategy and identification. Section IV describes the data used in estimation. Section V contains the results of our model, including parameter estimates, simulated marginal effects, and evidence on fitting the distributions. Section VI contains a brief discussion of policy implications, and Section VII concludes. Additional details on the theoretical model, conditional density estimation, and variable construction are available in appendices A, B, and C respectively.

II A Simple Two-Period Model of Medical Care Demand

A Model Specification and Assumptions

The change in health can affect the individual's optimization problem in two distinct ways. First, utility from contemporaneous health, H, and consumption, z, may be reference dependent with respect to health in previous periods.[2] For example, an individual who had been wheelchair bound but is now able to walk with the aid of a walker will feel better about her current health than someone in a similar walker who in the prior period was running marathons. In addition, the individual who is experiencing a decline in health may get more or less utility from other consumption (e.g., a burrito, a tennis racket) than the individual who is experiencing an improvement in health. The direction (sign) of the cross-partial derivative of utility from consumption with respect to change in health is an empirical question.[3] Denoting utility, U, and , A for the change in health from some prior reference point, we assume that $\frac{\partial U(\cdot)}{\partial A} \geq 0$, or that the marginal effect of change in health on utility is increasing in the change in health. Our assumption differs from much of the literature on reference-dependent preferences, which typically assumes the utility function from gains and losses is S-shaped. However, unlike wealth, health is bounded below by death. Strong loss aversion as health approaches the minimum health threshold will make utility from losses concave.

Second, changes in health from a reference point provide noisy signals about future health shocks.[4] We incorporate this signal value into our two period model by making

[2] Evidence is mixed on whether reference points are formed using rational expectations (Koszegi and Rabin, 2006) or adaptive expectations (Baucells et al., 2011). We use adaptive expectations, meaning reference health is defined by recent health history. Behaviorally, this implies the individual's reference health is the level of health to which the individual is accustomed. When we talk about "change in health" we mean change in health from this prior, reference health.

[3] The sign of the cross partial of utility from consumption and the state of health is also an empirical question for which there is currently no consensus in the literature. See Edwards (2008) and Finkelstein et al. (2009) for discussions and reviews of the empirical literature on health-dependent utility.

[4] Theoretical models of medical care demand that incorporate uncertainty in health (Cropper, 1977; Liljas,

the health shock in the second period (δ_2) a function of the change in health in the first period, A_1 (subscripts denote the time periods). We allow that $\frac{\partial \delta_2}{\partial A_1} \geq 0$, or that a negative (positive) change in health is associated with a future health decline (improvement).

We make two additional modifications to the standard health production function in the literature. First, we allow the level of health to be an element in health production, $\alpha(\cdot)$. We assume a concave relationship between health and health production: $\frac{\partial \alpha}{\partial H} \geq 1$ and $\frac{\partial^2 \alpha}{\partial H^2} \leq 0$. Given that co-morbidities reduce the effectiveness of medical care, the marginal effect of medical care on health should be smaller when the individual is in poor health. Second, we model health decay as an additive, periodic shock rather than a multiplicative rate. Unlike the multiplicative specification, this specification allows individuals in good and poor health to experience equally large (or small) changes in health.[5]

Individuals enter the first period knowing their initial health and wealth. They choose medical care and consumption to maximize first period utility and expected second period utility. After their choice of medical care and consumption, individuals experience a health shock prior to the end of the first period. At the end of the first period individuals know the net effect of their health investment minus the shock, and how their health has changed from referential initial health. First period health also contributes to their second period health production function. By restricting

1998; Picone et al., 1998; Ehrlich, 2000; LaPorte and Ferguson, 2007) or of the productivity of medical care (Dardanoni and Wagstaff, 1990) generally conclude that uncertainty results in a reserve stock of health and otherwise does not change the implications of the models from a deterministic specification. Since rigorously modeling uncertainty requires additional notation and mathematical complexity without resulting in additional useful intuition we present a deterministic specification even though we heuristically discuss uncertainty and incorporate uncertainty in the econometric implementation.

[5]The multiplicative functional form for health decline is common in the literature. However, this modeling assumption predicts an asymptotic decline in health (like a gentle ski slope) as a higher rate multiplied by declining health stock results in a smaller and smaller amount of health change. See Galama (2011) Figure 5 top left panel for an illustration of the decline in health from a simulation using the multiplicative functional form for health decline. Modeling health decline as an amount rather than a rate is more consistent with the observed longer duration of high health followed by a steeper decline in health towards the end of life (like a cliff).

ending wealth to zero, the individual's choice of medical care in the second period fully determines their choice of consumption. The second period utility is then determined by non-medical consumption, the resulting second period health, and the deviation of this second period health from the average of initial and first period health.

With this timing of the model and end-point assumptions we can specify a fully recursive utility function. For simplicity, we restrict second period wealth to zero, but we allow for savings from the first period reflected in the Lagrangian multiplier, λ^R, on the first period wealth constraint. Finally, in order to maintain the focus on the change in health, we treat income, y, as exogenous. Modeling income as a function of health would result in additional terms in the equilibrium condition reflecting the marginal benefit of health to wealth without adding to the intuition on the mechanisms associated with health dynamics. Details of the model and derivation of the equilibrium conditions below are available in Appendix A.

B Equilibrium Conditions

Solving the model recursively, we derive the equilibrium conditions governing the demand for medical care in the first period (first line) and second period (second line).[6]

(II.1)

$$\frac{\partial \alpha_2}{\partial H_1}\left(\frac{\partial U_2}{\partial H_2}+\frac{\partial U_2}{\partial A_2}-\frac{1}{2}\frac{\partial U_2/\partial A_2}{\partial \alpha_2/\partial H_1}\right)+\frac{\partial U_1}{\partial H_1}+\frac{\partial U_1}{\partial A_1} = \frac{\lambda^R P^m}{\partial \alpha_1/\partial m_1}+\frac{\partial \delta_2}{\partial A_1}\left(\frac{\partial U_2}{\partial H_2}+\frac{\partial U_2}{\partial A_2}\right)$$

$$\frac{\partial U_2}{\partial H_2}+\frac{\partial U_2}{\partial A_2} = P^m\frac{\partial U_2/\partial z_2}{\partial \alpha_2/\partial m_2}$$

In our simple two period model, the first expression in equation II.1 can be interpreted as the equilibrium demand for health investment comparable to equation (13) from Grossman (1972), equation (13) from Ehrlich and Chuma (1990) or equation (15)

[6]See Kohn and Patrick (2012) for a complete discussion of the model specification, first and second order conditions and comparative dynamics.

from Galama (2011).[7] In all of these models, a decline in health results in an increase in the marginal benefits from health due to the assumption of concave utility. The critical difference is that in prior work, the rate of depreciation is added back to the cost of health capital.[8] As a result, higher rates of depreciation increase the cost of health capital at the same time as the resulting lower level of health increases the marginal benefits from health. There is no inevitable disequilibrium in the extant models that could explain large investments in medical care.[9]

Our specification illustrates the mechanisms whereby different reference points would elicit different amounts of medical care demand among individuals with the same current level of health. Individuals with the same level of health may reach their health state from different values in previous periods. Those experiencing a greater decline in their health would have a greater marginal benefit to utility and thereby a greater disequilibrium and greater demand for medical care than those with smaller changes in their health.[10] Again this reflects an intuition that individuals are better able to adapt to small declines in their health than large ones (Groot, 2000). This utility value of the change in health is magnified by the assumption that health is an element in health production. Furthermore, if the change in health is a signal to future

[7]We agree with Galama (2011) that the first-order condition resulting from maximizing utility with respect to health investment, can be interpreted equivalently as the equilibrium condition for the health stock or for health investment.

[8]The corresponding notation in Grossman and Ehrlich and Chuma is δ and dt in Galama, both symbols defined as a rate of depreciation that is independent of health but assumed to increase with age. These three models all include the marginal effect of health on income (W, the wage rate, in Grossman and Ehrlich and Chuma and the more general ϕ_H marginal production benefit of health to wealth in Galama). A corresponding marginal benefit of health to wealth would appear in the same way in our specification if we were to relax our assumption of exogenous income. Finally our model has abstracted from discounting and time preference to simplify notation and focus on the change in health.

[9]Grossman notes the indeterminacy of medical care demand on p. 238: "... gross investment might increase, remain constant, or decrease. This follows because a rise in the rate of depreciation not only reduces the amount of health capital demanded by consumers but also reduces the amount of capital supplied to them by a given amount of gross investment."

[10]Although this implication differs from the standard S-shaped value in gains and losses from prospect theory, Kahneman and Tversky (1979) posit examples where the value function may take different shapes. One such example involves critical thresholds in wealth, i.e. a loss sufficient to lose a house. In our application, health is bounded below by some minimum threshold necessary for life. Strong loss aversion near the death point explains the increasing magnitude in marginal utility.

changes, then this signal value further reduces the marginal cost of health investment.[11]

In our specification where health decline is modeled as an amount rather than a rate, decline in health from a reference level causes an inevitable disequilibrium between marginal benefits and marginal costs. Equilibrium can only be restored with increasing amounts of medical care. The marginal productivity of medical care ($\partial\alpha/\partial m$) decreases with increasing amounts of medical care, reflecting diminishing returns to health investment.[12] Increasing consumption of medical care increases the cost of health capital (right hand side) bringing costs into balance with increasing marginal benefits (left hand side).

Allowing health to be an element in health production adds an additional term to the utility value of health (the first term in equation II.1) or alternatively can be subtracted from the cost of health.[13] The marginal productivity of health to health investment, ($\partial\alpha_2/\partial H_1$), which is not modeled in most of the extant literature, increases the inequality between marginal costs and benefits as health declines.

Comparing the equilibrium conditions for the two periods illustrates the difference between forward looking (period 1 condition) and myopic (period 2) medical care demand. The additional terms in the period one condition reflect the future value of health investment in terms of future health production and the second-period signal value. However, even without these forward looking terms, the gain/loss utility results in different demands for medical care among individuals with the same level of health.

Finally, these equilibrium conditions can also explain the observation that individuals with the same level of health but different levels of wealth demand different amounts of medical care. In both periods, higher levels of wealth result in lower costs

[11] We have modeled the health shock as a positive amount subtracted from health net of health investment. Thus, this shock gets larger as health declines more resulting in a negative derivative. Alternatively, if the health shock were modeled as a negative amount, then the derivative would be positive, but there would be a preceding negative sign resulting in the same interpretation of the signal value of the change in health.

[12] We agree with Ehrlich and Chuma (1990) and Galama (2011) that the assumption of a diminishing returns-to-scale health production function is necessary to ensure the determinacy of the model.

[13] This first term is unambiguously positive because $\partial\alpha/\partial H \geq 1$ and therefore $\frac{\partial U_2}{\partial A_2} > \frac{1}{2}\frac{\partial U_2/\partial A_2}{\partial\alpha_2/\partial H_1}$.

of investment by reducing the numerators of the first cost term (the shadow price of wealth declines with higher levels of wealth, and the marginal utility of consumption declines with higher levels of consumption).[14] Thus, the more wealth, the lower the marginal costs of health investment and the greater the demand for medical care necessary to achieve equilibrium. Furthermore, this wealth component in the equilibrium demand also confirms that the demands for medical care and consumption should be estimated jointly, rather than assumed separable.

The central hypothesis of this model is that individuals will demand more medical care the greater their decline in health at any level of health, age, or wealth. This mechanism can explain why relatively young and healthy individuals are observed in the upper tail of the medical care spending distribution, and conversely why all old and sick individuals are not in the top 5 percent.

III Econometric Implementation

Our specification captures how reference health and health dynamics affect the joint decision to consume medical care and other consumption, and how this decision in turn affects health in future periods.[15] Our estimation strategy is chosen with an eye to testing the key theoretical hypothesis of the model and simulating the full distribution of medical care spending rather than merely estimating mean or median effects.

A Timing Assumptions

The timing of the empirical model is similar to that introduced in the theoretical model in Section II. We assume that the individual enters each discrete period knowing her exogenous characteristics, $\mathbf{X}_t$, including age, gender, marital status, education, etc.

[14]Both period equilibrium conditions would have the same specification with λ^R had we not made the simplifying assumption that R2=0 and instead included the wealth constraint in the second period.

[15]We also empirically model death as a probabilistic outcome of individuals' health and medical care consumption, but it is not the emphasis of our research.

She also knows her endogenous health state, H_t, and all past realizations of health and medical care consumption $[H_{t-k}, m_{t-k}] \forall k \in \{1, \cdots, t\}$. The theoretical model shows that an individual's utility from health is reference dependent with respect to health in prior periods. When we refer to "change in health" in this section, we refer to a difference in contemporaneous health from the reference level of health as determined by the individual's health history. Specifically, change in health is the difference between contemporaneous health and the average level of health from the prior two periods.[16]

Knowing their demographics, current and past health as well as the functional forms on utility (unknown to the econometrician) for the health production function, the individual then chooses medical care and consumption to maximize lifetime utility. Because change from reference health is in the utility function, change in health is included in the expressions for both the demand for consumption and the demand for medical care.[17] Thus, the joint demand for consumption and medical care can be expressed as follows:

$$\begin{aligned} z_t^* &= z(H_t, A_t, m_{t-1}, z_{t-1}, \mathbf{X_t}, \epsilon_t^z) \\ m_t^* &= m(H_t, A_t, m_{t-1}, z_{t-1}, \mathbf{X_t}, \epsilon_t^m), \text{ where} \\ A_t &= H_t - \frac{1}{p}\sum_{i=1}^{p} H_{t-i} \end{aligned} \tag{III.1}$$

where $\epsilon_t^{z,m}$ is a preference shock and p is the number of periods over which historical health index values are averaged to form the reference level of health. These choices

[16] In preliminary examinations, we found that our results strengthen as we increase the number of periods used to form the reference level of health (e.g., average of last three, four periods, etc.) However, including more periods in the formation of reference health has a considerable effect on our sample size and worsens the initial conditions problem. We therefore believe the results reported here may understate the importance of reference health in explaining the top tail of medical care consumers.

[17] This specification is consistent Koszegi and Rabin (2006) where utility of consumption c, conditional on reference point r is defined as: $u(c|r) = m(c) + n(c|r)$, or the sum of utility of final consumption and the gain/loss relative to the reference level.

then affect health at the start of the next period:

$$H_{t+1} = \alpha(H_t, A_t, m_t, z_t, \mathbf{X_t}, \epsilon_t^H) \quad \text{(III.2)}$$

To maintain a reasonably parsimonious (and identifiable) model that focuses on the effect of the change in health on predicting the top tail of the medical care spending distribution, we do not model all of the possible mechanisms included in the literature.[18] First, we do not model the choice of insurance. Insurance choice is clearly endogenous to health status and the demand for medical care. However, insurance choice is also highly constrained by employment (under age 65) and the presence of universal Medicare coverage (over age 65) in addition to income (Medicaid eligibility). Second, in this specification, we do not model endogenous labor market choice, particularly retirement. We include variables on employment, insurance status, age, and income in the model. Table IV contains the full list of variables included in each expression.

B Identification

The empirical identification of this model comes through three sources. First, we make some intuitively reasonable exclusion restrictions. Our theoretical model implies that the change in health from some reference level of health to which the individual is accustomed, affects the demand for medical and non-medical goods. However, for predicting the health transition, the information from the individual's health history and lagged consumption of medical and non-medical goods is captured by the individual's contemporaneous health state. Conditional on the individual's realized contemporaneous health state, only current period consumption of medical and non-medical goods and a stochastic shock will determine the individual's health in the next period. Similarly, the individual's income and wealth should affect her demand for medical and

[18] See Hugonnier et al. (2013) Table 3 for an excellent summary of the major modeling choices in much of the literature.

non-medical goods, but not otherwise affect her health in the next period.

Second, the model is identified through the timing. However, to appeal to the timing assumption, we must specify endogenous initial conditions for the health states that form the reference level and initial demand for medical and non-medical goods:

$$
\begin{aligned}
H_1 &= H_1^i(\mathbf{X_1}, \mathbf{X^i}) \\
H_2 &= H_2^i(\mathbf{X_2}, \mathbf{X^i}, H_1) \\
m_2 &= m_2^i(\mathbf{X_2}, \mathbf{X^i}, H_1) \\
z_2 &= z_2^i(\mathbf{X_2}, \mathbf{X^i}, H_1)
\end{aligned}
\tag{III.3}
$$

$\mathbf{X_i}$ is a set of variables only included in the initial conditions: whether the respondent was a veteran, the respondent's number of living parents, the current/final age of those parents, and a vector of occupational stress measures. Ceteris paribus, individuals who worked in occupations which were more physically demanding, required heavy lifting, or exposed them to more environmental risk should have worse health and be consuming more medical care at the time we first observe them. Details on the construction of these occupational stress measures are discussed further in Appendix C. See Table IV for the variables in each equation. Finally, some identification is attained by the non-linearity of all expressions in the model.

C Conditional Density Estimation

We employ Conditional Density Estimation (CDE) to estimate the joint distribution of medical care expenses, consumption, the health transition, and initial conditions (Gilleskie and Mroz, 2004). For our purposes, CDE provides three advantages. First, CDE enables us to match any moment of the distribution of each variable, not just the conditional mean or conditional median. Second, CDE does not require parametric assumptions on the distribution of the error terms, enabling us to flexibly model left or right skewed distributions. (Section IV shows that both medical care spending and consumption are left skewed while health is right skewed.) Third, CDE permits the marginal effect of explanatory variables (including change in health) to vary over the support of the dependent variable for each equation in the model. In other words, we can capture whether the change in health may have a stronger effect in the top tail of the distribution of medical care consumption than at the mean. These features of CDE make it well suited for our research objective, to explain the top tail of the medical care spending distribution. Additional details on CDE are contained in Appendix B.

D Discrete Factor Random Effects

For each expression, we utilize a flexible random effects estimation technique that permits time-invariant and time-varying unobserved heterogeneity without imposing distributional assumptions on the error term. We approximate the joint distribution of both permanent and time-varying unobservables with a step function (Heckman and Singer, 1984). In Monte Carlo simulations, the discrete factor random effects estimator has been shown to reduce bias relative to the assumption of joint normality in the distribution of unobserved heterogeneity (Mroz, 1999).

We include a time-invariant, permanent unobserved heterogeneity component that may influence an individual's joint choice of medical care and non-medical consumption, and subsequent health transitions. For example, individuals who heavily value the future may be likely to invest in more medical care, engage in lower consumption, and enjoy persistently good health. Alternatively, individuals who are genetically predisposed to poor health may consume more medical care and experience more rapidly deteriorating health. Empirically, the distribution of medical care spending is strongly persistent within individuals over time, and modeling this unobserved heterogeneity will help us capture that (French and Jones, 2004; Cohn and Yu, 2012; Kohn and Liu, 2013).[19] The time varying component of heterogeneity is meant to capture changes

[19] Skewness and persistence within individuals are features of both total and out-of-pocket expenditures in the U.S. despite a population uninsurance rates near 10 percent.

that affect unobservable factors on a per-period basis. Hypothetically, if an individual is battling depression, she may consume less medical care, consume less non-medical goods and experience deterioration in health. We can therefore decompose the errors in each equation into three components:

$$\epsilon_t^j = \mu^j + \nu_t^j + e_t^j \qquad \forall j \in z, m, H \tag{III.4}$$

where μ^j captures the permanent heterogeneity for each expression, ν_t^j captures the time-varying component, and e_t^j represents the remaining i.i.d. Type-1 Extreme Value error necessary to formulate the logit hazard probabilities. Errors for the initial conditions expressions do not include time-varying heterogeneity as they are only observed once.

The likelihood function includes eight expressions: the per-period demand for medical care, non-medical consumption, the health transition equation, a per-period probability of death, two initial conditions equations for health (initial health and second period health, in order to formulate the two period health history) and initial conditions for the demand for medical care and consumption. Our actual estimation procedure therefore consists of a joint CDE estimation nested in a finite mixture framework. The individual's contribution to the likelihood function can be expressed as:

(III.5)

$$
\begin{aligned}
L_i(\Theta,\Psi,\Pi) = \sum_{k=1}^{K}\pi_k \Bigg[& \prod_{j_{h1}=1}^{J_{h1}} P(H_1 = j_{h1}|\mu_k^{H_1})^{1(H_1=j_{h1})} \prod_{j_{h2}=1}^{J_{h2}} P(H_2 = j_{h2}|\mu_k^{H_2})^{1(H_2=j_{h2})} \\
& \times \prod_{j_{m2}=1}^{J_{m2}} P(m_2 = j_{m2}|\mu_k^{m_2})^{1(m_2=j_{m2})} \prod_{j_{z2}=1}^{J_{z2}} P(z_2 = j_{z2}|\mu_k^{z_2})^{1(z_2=j_{z2})} \\
& \times \prod_{t=3}^{T_i}\sum_{l=1}^{L}\psi_l \Big[\prod_{j_m=1}^{J_m} P(m_t = j_m|\mu_k^m,\nu_{lt}^m)^{1(m_t=j_m)} \prod_{j_z=1}^{J_z} P(z_t = j_z|\mu_k^z,\nu_{lt}^z)^{1(z_t=j_z)} \\
& \times \prod_{j_H=1}^{J_H} P(H_t = j_m|\mu_k^H,\nu_{lt}^H)^{1(H_t=j_H)} \prod_{D=0}^{1} p(death = D|\mu_k^D,\nu_{lt}^D)^{1(death=D)} \Big] \Bigg]
\end{aligned}
$$

where Θ is the vector of parameters to be estimated from equations III.1, III.2, and III.3; ψ_l are the mixing parameters for the time-varying heterogeneity, and π_k are the mixing parameters for the permanent heterogeneity. K and L represent the number of mass points for the distribution of permanent and time-varying heterogeneity, respectively; and t indexes the waves in the data for each individual. The terminal time, specified T_i, reflects that not all individuals are observed in the sample for the same number of periods. $J_{h1}, J_{h2}, J_{m2}, J_{z_2}, J_z, J_m$, and J_H are the number of cells for each conditional density estimation.

IV Data

We estimate the model using the RAND files of the Health and Retirement Study (HRS), a longitudinal biennial panel survey of individuals 50 years old and over, from 1992-2010. The HRS is well suited for our purposes as it contains data on all the relevant variables over a sample period sufficient to capture the dynamic evolution of health, demand for medical care, and consumption. However, the HRS is limited in that it excludes those under age 50, so we are unable to fully capture the population-wide age distribution of the top 5 percent of medical care consumers, of which nearly

40 percent were younger than 55 in 2009 (Schoenman, 2012).

In order to estimate the model with valid initial conditions, we restrict the sample to those individuals who are observed for at least three periods. With this restriction, we have a sample of 173,312 observations comprised of 25,872 individuals. Table I contains information on the number of individuals we observe for a given number of waves. We observe individuals for an average of 7 waves. Summary statistics of our sample are available in Table II. A few characteristics of the sample are worth mentioning. Particularly for their generation, the individuals in the sample are well educated, with 68 percent of the sample graduating high school and 18 percent graduating from college. Also, most individuals in the sample had stable careers, with an average tenure in their longest held occupation of over 20 years. Also note that annual consumption exceeds annual income. This is reasonable because the median individual in the sample is past retirement age and presumably dissaving.

RAND HRS includes two measures of medical care expenditures: out-of-pocket medical care expenditures and total medical care expenditures. We use out-of-pocket medical care expenditures for three reasons. First, the total medical expenditure information was collected by asking respondents about the amount of total medical care expenditures they thought they incurred, without any external validation for the answers provided. As insured individuals are notoriously insulated from their true total costs, the variation around reported out-of-pocket expenditures was very large and seemingly random.[20] Second, total medical expenditures are documented only for the first six waves, so using total medical expenditures would halve the number of observations. Third, because we are concerned with the individual's optimization problem, the out-of-pocket expense reflects the cost to the individual. Even with insurance those over (under) 65 still spend approximately 16 percent (10 percent) of disposable income on medical care (Desmond et al., 2007; Banthin and Bernard, 2010).

[20]Reported total medical expenditures has 16 times the variance of out-of-pocket medical expenditures. The two variables share a correlation coefficient of 0.14

The RAND HRS files include many categorical variables for level of difficulties with activities of daily living (ADL's), instrumental activities of daily living (IADL's), chronic conditions, self-reported health, and other data on the respondent's health. We convert these discrete categorical variables into a single index of "health" using Multiple Correspondence Analysis (MCA).[21] Index variables and weights used to construct this measure are in Table III.[22] The transformation of several discrete indicators into a continuous index reduces the impact of problematic unobservable cut-point and adaption heterogeneity often associated with self-assessed health and other discrete health measures.[23] In addition, a single health index makes computing the change in health more tractable.

We calculate consumption of the aggregate good by subtracting change in non-housing financial wealth and out-of-pocket medical expenses from income. This calculated variable represents consumption-net-of-savings. However as most individuals in the data set are approaching or past retirement age, dissaving is more common than saving. Additionally, we cannot capture the effects of capital gains. [24]

We are primarily interested in estimating the conditional joint distributions of three variables: health status, out-of-pocket medical care expenditures, and non-medical care consumption. From the descriptive statistics and the graphs of the kernel densities of these variables (see Figure 1), we see that the distributions of medical care expenditures and non-medical consumption are skewed left, but the distribution of the health index is skewed right. These observations are intuitive. Most people are fairly healthy and medical care expenditures and consumption are driven by right-tailed income and

[21] MCA is used to transform discrete variables into a single continuous variable, whereas Principal Components Analysis is used to transform continuous variables into a single continuous variable. See Kohn (2012) for a full description of the MCA health index methodology.

[22] There is considerable multimodality at the top of the health index distribution as many individuals report having just one ADL, or one chronic health condition, or "very good" health.

[23] See Contoyannis et al. (2004) for a full discussion of the problems associated with self-assessed health.

[24] The median person in our sample has non-housing financial wealth of $10,500 and a person in the 90^{th} percentile of wealth has $250,000 in non-housing financial assets. Except for the upper tail of the wealth distribution, unobserved capital gains are a minimal concern in calculating consumption.

wealth distributions. These skewed distributions underscore the importance of modeling the full distribution, rather estimating the conditional mean. In our sample, the top 5 percent of medical care consumers account for 46 percent of all medical care, consistent with the population observation that motivates our study.

V Results

Parameter estimates from the joint CDE estimation are in Tables V-IX. We have estimated the model with three mass points in the support of permanent heterogeneity and two points of time-varying heterogeneity.[25] Overall, we fit the highly skewed distributions of medical care, consumption, and health reasonably well (see Figure 1). Because the estimates are for parameters in non-linear hazard probabilities they are not directly interpretable without numerical simulation. We therefore discuss the key marginal effects below. Tables X and XI report marginal effects for the balance of the variables of interest. Recall that one benefit of using CDE is that we can estimate marginal effects at different points of the distribution of the dependent variable. Some of the variation in these marginal effects stems from explanatory variables having different local effects on the probability of being observed in a given part of the distribution. Tables V-IX therefore contain three parameter estimates for each variable of interest. For some variables, the marginal effect is positive in the low end of the distribution of the dependent variable, and negative in the top portion of that same distribution, or vice versa.[26] For each variable in each expression, we report three marginal effects: one for the effect of the explanatory variable in the lowest quartile of the dependent vari-

[25] Adding additional mass points does not significantly imcrease the likelihood function, as vetted with an LR test (p-value = 0.21).

[26] Marginal effects are calculated by replicating each observation in the data 80 times. We forward simulate the data using the observed values of the exogenous variables and estimated parameters of the model. We then change a variable of interest, and re-simulate the data still using the estimated parameters of the model and holding all other exogenous variables fixed. Continuous variables are increased by adding 10 percent to their previous value. Marginal effects of binary variables are calculated by simulating twice - once with all observations set to zero, once with all observations set with a value of one.

able, one for the effect of the explanatory variable in the top quartile of the dependent variable, and a third marginal effect for the interquartile range. Each marginal effect is the mean percentage change in the value of the dependent variable, conditional on the dependent variable being observed in that quartile.

For interpretation, consider the marginal effect of having insurance on medical care consumption (left column of Table X). The marginal effect of having insurance on out-of-pocket medical care expenditures is negative (-3.1 percent) among those who are in the lowest quartile of medical care consumers. The marginal effect of having insurance on out-of-pocket medical expenditures is still negative in the interquartile range (-2.6 percent), but positive in the top quartile of medical care consumers. We interpret this as evidence that the price elasticity of medical care demand may be increasing in individuals' medical care expenditures. Alternatively, those who spend the most on care may also face the most binding budget constraint. To take another example, the effect of education on medical care expenditures is negative across the distribution, consistent with education increasing health productivity. The magnitude of the marginal effect of education increases from -1.0 percent at the bottom quartile to -11.5 percent at the top. This monotonic but non-linear effect over the distribution is intuitive as those who spend more have more to gain (or in this case save) by being more savvy and productive consumers of medical care.

A Empirical Evidence on the Effects of Reference Health

The critical finding is that even after controlling for contemporaneous health, reference health significantly affects the demand for medical care.[27] By simulating the model, we find that a 10 percent decline in health from reference health results in a 22 percent increase in the probability that an individual is in the top 5 percent of

[27] In the kernel of expression that enters the hazard probability in CDE, the arguments for H_t and A_t are additively separable. A_t, change in health, is the difference between H_t and reference health. Conditional on current health, the effect of a decrease in health is therefore algebraically equivalent to the effect of an increased level reference health.

medical care consumers. Over the entire distribution of medical care demand, a 10 percent decline in health from reference level health increases expected medical care consumption by 14 percent. We also find that the effect of a change in health from reference levels on demand for medical care is increasing in the size of the change. A one percentage point decline in health leads to a 2 percent increase in the probability of being in the top 5 percent, and an overall 1.3 percent increase in expected medical expenditures. However, a 20 percentage point decline in health leads to a substantially larger 48 percent probability of being observed in the top 5 percent, and a 31.2 percent increase in overall medical care expenditures. The marginal effects of an improvement in health are smaller in magnitude than those of a decline. A 10 percentage point improvement in health decreases the probability that an individual is observed in the top 5 percent by 19 percent, and overall medical expenditures decrease by 13 percent. All of these results are consistent with loss aversion, as advanced by Kahneman and Tversky (1979).

For perspective, we compare the effects of a change in health to the pure effect of contemporaneous health alone. If we decrease contemporaneous health and reference health by 10 percent (thereby holding A_t constant) the probability that in individual is observed in the top 5 percent of the medical care spending distribution increases by 44 percent. Thus, the level of health is clearly important, but reference health and health dynamics compound the effect of contemporaneous poor health on high medical care demand.

B Matching the Individuals and Demographics of the Top 5 Percent

In order to determine which individuals are likely to be in the top 5 percent of medical care consumers, we again simulate the model, replicating each observation in the data 80 times. In simulation, we use the model to generate predictions and then compare the predictions of the model to the observed data.[28] From a policy perspective, the primary contribution of our model and empirics is improved prediction of dynamic health investment and matching the top 5 percent of medical care consumers. For comparison, a lagged dependent variable regression of medical care consumption on the exact same arguments used in CDE yields an overall R-squared of 0.06. In other words, at the conditional mean, the covariates available to us explain 6 percent of the variation in medical care consumption. Using 6 percent as a bench mark, our model represents improvement if it generates a match rate that is 6 percent greater than random.

Simulating the model as described above, our model generates a 14.5 percent match rate between predicted and observed individuals in the top 5 percent of medical care consumers. We also have estimated this model under a specification consistent with the Grossman model, one which does not include a reference level of health, nor lagged medical care or aggregate consumption. This specification where only contemporaneous state variables enter the utility function generates an 8.5 percent match rate of predicted and observed individuals in the top 5 percent of medical care. Therefore, our model outperforms the Grossman-consistent model in matching by 65 percent.

To gauge our model's effectiveness in fitting the full distribution of medical care consumption, we create an indicator variable for whether an individual's predicted medical care consumption is within a 10 percentile range of the individual's observed medical care consumption. For our model, this +/- 10 percentile match rate is 36 over the top quartile and 29 percent over the total distribution. When an individual's predicted and observed health indices are within 10 percentiles of one another, the match rate for the top quartile improves to 41 percent and total match rate improves

[28] We randomly draw each replication's permanent type for all periods, a time-varying joint shock for each period, and an idiosyncratic draw from the uniform distribution. We then use the individual's exogenous variables and the estimated parameters of the model to forward simulate the individual's health state transitions and decisions to consume medical care and non-medical goods. We compare the averaged outcomes of these simulated individuals to the observed decisions and outcomes in the data.

to 32 percent.

One of the primary motivations for including reference health in the utility function is to help explain why individuals who are relatively young and healthy are among the top 5 percent. To gauge the model's effectiveness in capturing this phenomenon, we compare the summary statistics for individuals predicted to fall in the top 5 percent by our model and a Grossman-consistent model to the observed data. These summary statistics are exhibited in Table XII. We match the observed data more closely than the Grossman-consistent model on most dimensions. We more closely match the mean age in the top 5 percent. Our predicted mean age in the top 5 percent is three years younger than the Grossman-consistent model, thus, we better match young people in the top 5 percent. We also better match relatively healthy people in the top 5 percent. In the observed data, mean health among the top 5 percent of medical care consumers is 0.636, compared to our predicted mean health in the top 5 percent of 0.456 and the Grossman-consistent prediction of only 0.26.

C Empirical Evidence on Complimentarity of Medical Care, Health, and Consumption

Previous literature has found conflicting results on how the individual's health state affects the marginal utility of consumption (see Finkelstein et al. (2009), p. 117 for a review). Edwards (2008) and DiNardi et al. (2010) find a negative cross-partial between health and marginal utility from consumption suggesting the two are substitutes, while Finkelstein et al. (2013) and Viscusi and Evans (1990) find a positive cross-partial suggesting complementarity. This is not surprising, given than an increase in health may yield two separate effects on the individual's solution to her optimization problem. First, health may positively affect the utility from consumption (the fries taste better because I am healthier). However, health may reduce observed consumption via the dynamic budget constraint. Ceteris paribus, if individuals are consumption smoothing and expect to live longer, we expect them to consume less today. Empirically, the effect of health on consumption should be determined by which effect dominates.

In our model, reference health and change from reference health are defined entirely by health dynamics. While the effects of reference health are our primary focus, the dynamics of health in and of themselves, yield auxiliary evidence on the complimentarity of health and consumption. By including both contemporaneous health and health dynamics in our expression for the demand for consumption, we find evidence of complimentarity and effects through the dynamic budget constraint. Specifically, we find that a 10 percent improvement in health leads to a 4 percent reduction in consumption, but that a 10 percent increase in current and previous health leads to a 3.5 percent increase in consumption. The latter supports the hypothesis that health and consumption are complements, whereas the former result is consistent with consumption-smoothing individuals operating under a dynamic budget constraint. Recall that most of the individuals in the HRS are very near or past retirement. The only way to fund additional years of life is by reducing consumption. A positive change in health should predict lower consumption due to greater expected longevity. However, the positive effect of level health on consumption suggests health and consumption are compliments. In other words, our results suggest that health and consumption are complements, but that the effect may be offset by health dynamics. Individuals experiencing an improvement in health may not consume as much as one would expect, due to the offsetting effect of the dynamic budget constraint.

VI Discussion

Our theory and empirical findings both help explain the stylized facts about who consumes high amounts of medical care. Recall that not all of these high users of medical care are old and sick, and not all those who are old and sick are high users. The key empirical finding is that conditional on current health, a 10 percent higher reference health makes individuals 22 percent more likely to be in the top 5 percent of medical care consumers. Our analysis suggests that relatively (un)healthy high users of medical care are distinguished from other relatively (un)healthy non-users by the level of health to which they are accustomed.

As with the variation in health status, our finding on the change in health can explain why although individuals over 65 are more likely to be in the top 5 percent, not all those over 65 are in the top 5 percent. Our analysis suggests that those seniors who experience larger losses in health are more likely to be in the top 5 percent, and those who were already in poor health are more likely still. Furthermore, the combination of large decreases in health, lower levels of health, and strong loss aversion as health approaches the minimum threshold among individuals at older ages can explain the observed increase in medical care when additional longevity is doubtful.

A focus on the change from reference health as a predictor of high medical care expenses has several policy implications. First, focusing on the change in health provides support for recent efforts to reduce frailty and support so-called healthy aging (Siven, 2012 and references therein). If seniors experience more gradual declines in their health, then they are more likely to stay out of the top 5 percent of medical care users. Second, while it is important to make sure that chronic conditions are well managed so that they do not “spike into acute conditions, our findings suggest additional focus on managing newly diagnosed health problems. For example, it may be that those who have been in good health but experience a significant health shock are less efficient in navigating the medical care system and thereby end up in the top 5 percent. Third, incorporating reference health into models of medical care demand has the potential to improve financial and operational forecasting, which can improve the efficiency of insurance products and medical care facilities.

VII Conclusion

We offer new theoretical and empirical insights into the predictors of high medical care expending. The distribution of medical care spending is highly skewed, with the top 5 percent accounting for nearly 50 percent of expenditures. Most previous work that estimates the distribution of medical care spending takes a classical approach. We find evidence that subjective and behavioral factors play a significant role in determining high medical expenditures. Specifically, our theoretical model suggests that the reference health can help to explain high medical care spending and better predict who will be high medical spenders. We find that individuals' medical care demand responds more strongly to losses than gains in health. We find that while reference health (or health dynamics) significantly affects medical care spending at all levels, the effects of reference health are particularly helpful in determining medical care usage at the top of the distribution. Using data from the HRS, the marginal effect of a 10 percent decline in health from reference levels is a 22 percent increase in the probability of being in the top 5 percent. Moreover, holding the 10 percent decline in health constant, but reducing the levels of both reference and current health by 10 percent increases the probability of being in the top 5 percent by 44 percent. When health states are close in the dynamic prediction of the model, we match the individuals in the top quartile of medical consumers at 41 percent and the top 5 percent at 18 percent. We believe further examination of behavioral factors that determine medical care consumption can uncover why a small number of people spend such large amounts on care. Understanding the behavior of these high spenders is the key to bending the cost curve.

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A Theoretical Details

We define the utility U, change in health A, health H and wealth R in each period, as follows:

$$
\begin{aligned}
U_1 &= u(z_1, H_1, A_1) \\
A_1 &= H_1 - H_0 \\
&= \alpha_1(m_1, H_0) - \delta_1 \\
H_1 &= \alpha_1(m_1, H_0) - \delta_1 \\
R_1 &= r_1 R_0 + y_1 + P_1^m m_1 - z_1
\end{aligned} \tag{A.1}
$$

where the subscripts indicate time, $\alpha(\cdot)$ is the health production function, and $u(\cdot)$ is the utility function. We can therefore express second period utility, health, change in health, and wealth in terms of first period state variables and choices:

(A.2)

$$
\begin{aligned}
U_2 &= u(z_2, H_2, A_2) \\
H_2 &= \alpha_2(m_2, H_1) - \delta_2(A_1) \\
&= \alpha_2(m_2, (\alpha_1(m_1, H_0) - \delta_1)) - \delta_2((\alpha_1(m_1, H_0) - \delta_1) - H_0) \\
A_2 &= H_2 - \tfrac{1}{2}(H_1 + H_0) \\
&= \big[\alpha_2(m_2, H_1) - \delta_2(A_1)\big] - \tfrac{1}{2}\big((\alpha_1(m_1, H_0) - \delta_1) + H_0\big) \\
&= \Big[\alpha_2(m_2, (\alpha_1(m_1, H_0) - \delta_1)) - \delta_2((\alpha_1(m_1, H_0) - \delta_1) - H_0)\Big] - \tfrac{1}{2}\Big((\alpha_1(m_1, H_0) - \delta_1) + H_0\Big) \\
R_2 &= r_2 R_1 + y_2 - P_2^m m_2 - z_2 = 0
\end{aligned}
$$

and the following additional constraints:

$$
\begin{aligned}
H_0 &> H_{min} \\
H_2 &> H_{min} \\
R_0 &> 0 \\
R_2 &\geq 0 \\
A_0 &= 0
\end{aligned} \tag{A.3}
$$

yielding a fully recursive specification:

(A.4)

$$
\begin{aligned}
&\max_{m_1,m_2,z_1} \textstyle\sum_t U(z_z, H_t, A_t) = \\
u\ &\Big[(r_2R_1 + y_2 - P_2^m m_2), \alpha_2(m_2, (\alpha_1(m_1, H_0) - \delta_1)) - \delta_2((\alpha_1(m_1, H_0) - \delta_1) - H_0), \\
&\Big[\alpha_2(m_2, (\alpha_1(m_1, H_0) - \delta_1)) - \delta_2((\alpha_1(m_1, H_0) - \delta_1) - H_0)\Big] - \tfrac{1}{2}\Big((\alpha_1(m_1, H_0) - \delta_1) + H_0\Big)\Big] \\
+ \quad u\ &\Big[z_1, (\alpha_1(m_1, H_0) - \delta_1), \Big((\alpha_1(m_1, H_0) - \delta_1) - H_0\Big)\Big] + \lambda^R(r_1R_0 + y_1 - P^m m_1 - z_1)
\end{aligned}
$$

where λ^R is the Lagrangian multiplier on the first period wealth constraint. We can first express first order conditions for medical care in periods 1 and 2 as:

(A.5)

Period 1:

$$
\begin{aligned}
&\frac{\partial U_2}{\partial H_2}\frac{\partial H_2}{\partial \alpha_2}\frac{\partial \alpha_2}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{\partial m_1} + \frac{\partial U_2}{\partial H_2}\frac{\partial H_2}{\partial \delta_2}\frac{\partial \delta_2}{\partial A_1}\frac{\partial A_1}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{\partial m_1} + 2 * \frac{\partial U_2}{\partial A_2}\frac{\partial A_2}{\partial H_2}\frac{\partial H_2}{\partial \alpha_2}\frac{\partial \alpha_2}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{\partial m_1} + \\
&\frac{\partial U_2}{\partial A_2}\frac{\partial A_2}{\partial H_2}\frac{\partial H_2}{\partial \delta_2}\frac{\partial \delta_2}{\partial A_1}\frac{\partial A_1}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{\partial m_1} + \frac{\partial U_2}{\partial A_2}\frac{\partial A_2}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{\partial m_1} + \frac{\partial U_1}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{m_1} + \frac{\partial U_1}{\partial A_1}\frac{\partial A_1}{\partial H_1}\frac{\partial H_1}{\partial \alpha_1}\frac{\partial \alpha_1}{\partial m_1} \\
&= \lambda^R P^m
\end{aligned}
$$

Period 2:

$$
\frac{\partial U_2}{\partial H_2}\frac{\partial H_2}{\partial \alpha_2}\frac{\partial \alpha_2}{\partial m_2} + \frac{\partial U_2}{\partial A_2}\frac{\partial A_2}{\partial H_2}\frac{\partial H_2}{\partial \alpha_2}\frac{\partial \alpha_2}{\partial m_2} = P^m \frac{\partial U_2}{\partial z_2}
$$

To simplify the above expression, we first recognize that:

(A.6) $$\frac{\partial A_2}{\partial H_2} = \frac{\partial A_1}{\partial H_1} = \frac{\partial H_2}{\partial \alpha_2} = \frac{\partial H_1}{\partial \alpha_1};\ \frac{\partial H_2}{\partial \delta_2} = -1;\ \frac{\partial A_2}{\partial H_1} = -\frac{1}{2}$$

and we can therefore rewrite the expressions in equation A.5 as:

$$
\begin{aligned}
\lambda^R P^m &= \frac{\partial U_2}{H_2}\frac{\partial \alpha_2}{\partial H_1}\frac{\partial \alpha_1}{\partial m_1} + \frac{\partial U_2}{\partial A_2}\frac{\partial \alpha_2}{\partial H_1}\frac{\partial \alpha_1}{\partial m_1} - \frac{\partial U_2}{\partial H_2}\frac{\partial \delta_2}{\partial A_1}\frac{\partial \alpha_1}{\partial m_1} - \frac{\partial U_2}{\partial A_2}\frac{\partial \delta_2}{\partial A_1}\frac{\partial \alpha_1}{\partial m_1} \\
&\quad - \frac{1}{2}\frac{\partial U_2}{\partial A_2}\frac{\partial \alpha_1}{\partial m_1} + \frac{\partial U_1}{\partial H_1}\frac{\partial \alpha_1}{\partial m_1} + \frac{\partial U_1}{\partial A_1}\frac{\partial \alpha_1}{\partial m_1} \\
P^m \frac{\partial U_2}{\partial z_2} &= \frac{\partial U_2}{\partial H_2}\frac{\partial \alpha_2}{\partial m_2} + \frac{\partial U_2}{\partial A_2}\frac{\partial \alpha_2}{\partial m_2}
\end{aligned}
\tag{A.7}
$$

Combining terms in equation A.7 and diving through by the marginal productivity of medical care $\partial\alpha_t/\partial m_t; t = 1, 2$ enables us to place the marginal benefit to medical care on the left hand side and the marginal cost of the right.

$$
\frac{\partial \alpha_2}{\partial H_1}\left(\frac{\partial U_2}{\partial H_2} + \frac{\partial U_2}{\partial A_2} - \frac{1}{2}\frac{\partial U_2/\partial A_2}{\partial \alpha_2/\partial H_1}\right) + \frac{\partial U_1}{\partial H_1} + \frac{\partial U_1}{\partial A_1} = \frac{\lambda^R P^m}{\partial \alpha_1/\partial m_1} + \frac{\partial \delta_2}{\partial A_1}\left(\frac{\partial U_2}{\partial H_2} + \frac{\partial U_2}{\partial A_2}\right)
\tag{A.8}
$$

$$
\frac{\partial U_2}{\partial H_2} + \frac{\partial U_2}{\partial A_2} = P^m \frac{\partial U_2/\partial z_2}{\partial \alpha_2/\partial m_2}
$$

B Conditional Density Estimation

CDE utilizes a sequence of conditional logit probability functions to approximate the density of the outcome of interest. First, we divide each variable of interest, y, into K quantiles containing equal numbers of observations in each "cell. For each interval, the k^{th} interval is defined by $[y_{k-1}, y_k)$. We define y_0 as the smallest observation and $y_K = \infty$. Following Gilleskie and Mroz (2004), we can express the conditional probability that the random variable Y falls into the first interval as:

$$
\lambda(1, x) = p[y_0 \leq Y < y_1 | x] = \int_{y_0}^{y_1} f(y|x) dy
\tag{B.1}
$$

Similarly, the probability that Y falls in the k^{th} interval can be expressed as:

$$p[y_{k-1} \leq Y < y_k|x] = \int_{y_{k-1}}^{y_k} f(y|x)dy \tag{B.2}$$

The conditional probability that the dependent variable is observed in the k^{th} interval, given that it is not observed in intervals 1 through $k-1$ can be expressed as:

$$\lambda(k,x) = p[y_{k-1} \leq Y < y_k|x, Y \geq y_{k-1}] = \frac{\int_{y_{k-1}}^{y_k} f(y|x)dy}{1 - \int_{y_0}^{y_{k-1}} f(y|x)dy} \tag{B.3}$$

Thus, the $\lambda(k,x)$ serves as a discrete hazard function, given the cut points k, the upper and lower bounds on Y and covariates x. As a hazard function, the probability that Y falls into the k^{th} interval is given by:

$$p[y_{k-1} \leq Y < y_k|x] = \lambda(k,x) \prod_{j=1}^{k-1} [1 - \lambda j, x] \tag{B.4}$$

As suggested by Gilleskie and Mroz (2004), we use a sequence of logit probabilities to form the hazard function, and thus the probability that our random variables of interest fall into a given cell. Additionally, we interact each covariate$x$ with a function of the interval number, $\gamma_k = -ln(K-k)$ and γ_k^2. These interactions between the γ terms and the covariates are what permit the marginal effect of the variable of interest to vary over the support of the dependent variable. For each expression in equations III.1-III.2 and for each cell $k \in \{1, \ldots, K\}$, we can form a linear function of our covariates and γ terms:

$$g^j(k,x) = \mathbf{X^j}\beta_1^j + \mathbf{X^j}\gamma_k\beta_2^j + \mathbf{X^j}\gamma_k^2\beta_3^j + \epsilon_t^j \ \forall j \in \{z, m, H, H_1, H_2, z_2, m_2\} \tag{B.5}$$

With some abuse of notation, $\mathbf{X^j}$ is inclusive of all variables in expression j. We can therefore form the logit probabilities used to form the hazard function as:

$$\lambda^j(k,x) = \frac{e^{g^j(k,x)}}{1 + e^{g^j(k,x)}} \tag{B.6}$$

and these terms are subsequently combined to form the estimable probabilities in equation B.4.

C Formation of Occupational Demands

The RAND HRS files contains limited information on respondents' employment history: a categorical response where individuals' self-identify as having primarily been engaged in one of 17 occupations and a variable for how long the individual held that occupation. The coarse occupation categories listed in the HRS correspond to subgroups of occupations from the 1980 Census Occupation Codes.

Data on the indices of occupational demands come from the 1991 Dictionary of Occupational Titles.[29] The DOT is produced by the department of labor and was designed to provide information on the skills/abilities required to perform an occupation. The DOT contains information on 12,686 "occupations" that are better characterized as 'tasks'. A supplement to the 1991 DOT contains information on the demands occupations place on individuals. There is a 5-category rating for required strength: Sedentary, Light, Medium, Heavy, and Very Heavy, corresponding to lifting/manipulating varying weights on the job with varying frequency. We numerically code Sedentary occupations with a strength requirement of 1 and a Very Heavy occupation with a strength requirement of 5.

In addition to strength, the DOT also contains information on the frequency with which occupations require climbing, balancing, stooping, kneeling, crouching, crawling,

[29]The 1991 DOT had changed little from the 1977 edition of the DOT. While there are newer, better data sets on occupational requirements (e.g., the O*NET) the 1977-1991 DOT is more relevant to the time where individuals in the HRS were working.

reaching and handling. For each occupation, each requirement was coded with one of the following values:

$$
\text{(C.1)} \qquad \begin{aligned}
0 &= \text{Not required} \\
1 &= \text{Required up to } 1/3 \text{ of the time} \\
2 &= \text{Required between } 1/3 \text{ - } 2/3 \text{ of the time} \\
3 &= \text{Required more than } 2/3 \text{ of the time}
\end{aligned}
$$

To form the numerical measure of physical demands of a given DOT occupation, we take the average over the numerical values assigned to each of the strength values in that occupation.

The DOT also contains information on the frequency with which occupations expose individuals to various adverse environmental conditions or other occupational hazards, including: weather, extreme cold, extreme heat, humidity, noise levels, vibration, poor breathing conditions, proximity to moving mechanical parts, electrical shock, unprotected heights, radiation, explosives, and caustic chemicals. These occupational hazards are coded with the same frequency values as the physical demands. The hazard exposure index for a DOT occupation is calculated by averaging over the reported frequencies for each occupation.

The job requirements supplement to the 1991 DOT also details which 1980 Census Occupation Code encompasses each DOT occupation. Calculating an HRS occupation index value is then a matter of averaging the strength, non-strength physical, and hazard exposure numeric values over all DOT occupations within each COC/HRS occupation.

The HRS also reports the amount of time a respondent worked in their selected occupation. If individuals who worked in physically intensive or hazardous occupations have more worn bodies by the time we observe them in the sample, individuals who worked more years in these arduous occupations should have more proverbial miles on them. We therefore multiply the HRS occupation values for strength required, physical demands, and hazard exposure by the respondent's reported number of years worked in that occupation. It should be noted that these variables, used for exclusion restrictions in initial conditions are intended as ordinal, rather than cardinal variables. The interpretation of having a hazard exposure of "5" is irrelevant. For our purposes, it is sufficient that individuals who have worked more years in more hazardous/arduous occupations experience better/worse health and higher/lower medical expenditures at the time of first observation.

Table I: Number of Observations Per Individual

Number of Individuals	**Number of Waves Observed**
2,389	3
4,568	4
1,856	5
1,778	6
4,380	7
1,381	8
2,355	9
7,120	10
Total Individuals	Average Observations Per Individual
25,827	6.949

The relatively high numbers of individuals observed for 4 & 7 are due to HRS adding respondents at waves 7 and 4 respectively

Table II: Summary Statistics

Variable	Mean	S.D.	Min	Max
Demographic Variables				
Female	0.575	0.494	0	1
Black	0.145	0.352	0	1
Hispanic	0.087	0.282	0	1
Other Non-White	0.021	0.142	0	1
Health Index	0.767	0.172	0	1
Age	67.190	10.526	50	109
Married	0.635	0.481	0	1
Widowed	0.192	0.394	0	1
Number of Children	3.166	1.977	0	8
Western Region	0.168	0.374	0	1
Midwest Region	0.240	0.427	0	1
Northeast Region	0.159	0.365	0	1
Number of Living Parents	0.272	0.530	0	2
Mothers Age (or Age at Death)	75.263	14.944	16	113
Fathers Age (or Age at Death)	71.390	14.397	12	113
Death	0.061	0.239	0	1
Education/Human Capital				
Highest Grade Completed	12.086	3.349	0	17
High School Graduate	0.693	0.461	0	1
Attended College (1+ years)	0.382	0.486	0	1
College Graduate	0.180	0.385	0	1
Tenure at longest job (years)	20.728	11.842	0	1
Veteran	0.237	0.423	0	1
Strength Required (primary occupation)	0.654	0.925	0	7
Physical Demand (primary occupation)	1.370	8.492	0	6
Exposure Factors (primary occupation)	0.291	0.284	0	3
Financial Information				
Insured	0.872	0.344	0	1
Non-Housing Wealth (100K units)	0.942	2.223	0	15.02
Annual Income (100K units, top coded)	0.491	0.538	0	5
Annual Out of pocket med. exp. (100K units)	0.029	0.102	0	12.06
Calculated Annual Consumption (100K units)	0.661	0.464	0	12.04
Individuals in Data Set	25,872			
T Number of Observations	173,312			

Table III: Health Index Weights

Variable	Weight
Self-Assessed Health	
Excellent	1.241
Very Good	0.802
Good	0.145
Fair	-1.056
Poor	-2.810
Index of Activities of Daily Living	
0	0.392
1	-1.677
2	-2.497
3	-3.00
4	-3.401
5	-3.489
Number of Chronic Health Conditions	
0	1.079
1	0.568
2	-0.047
3	-0.729
4	-1.484
5	-2.418
6	-3.277
7	-4.306
8	-4.317
CESD Mental & Emotional Index	
0	0.807
1	0.180
2	-0.467
3	-0.947
4	-1.227
5	-1.539
6	-1.987
7	-2.501
8	-2.854

Table IV: Table of Variables Included in each CDE expression

Variable	**Per-period Med. Care**	**Per-period Cons.**	**Per-period Health**	**Initial Med. Care**	**Initial Cons.**	**Initial Health**
Age	X	X	X	X	X	X
Age^2	X	X	X	X	X	X
Black	X	X	X	X	X	X
Female	X	X	X	X	X	X
Education	X	X	X	X	X	X
Region Indicators	X	X	X	X	X	X
# of Kids	X	X		X	X	X
Insured	X	X		X	X	X
Married	X	X		X	X	X
Income	X	X		X	X	
Wealth	X	X		X	X	
H_t	X	X	X			
A_t	X	X	X			
m_{t-1}	X	X				
z_{t-1}	X	X				
m_t			X			
z_t			X			
$H_t * z_t$			X			
$H_t * m_t$			X			
Education*m_t			X			
Veteran Status				X	X	X
Living Parents				X	X	X
Mother's Age				X	X	X
Father's Age				X	X	X
Physical Work				X	X	X
Hazard Exposure				X	X	X
Strength Required				X	X	X

Table V: CDE Parameter Estimates for Per-period Medical Care Expenditure

Variables	**X**		**Xγ**		**Xγ^2**	
	Estimate	Std. Err	Estimate	Std. Err	Estimate	Std. Err
Constant	-4.808	***0.200	1.098	***0.194	0.035	0.058
Health	1.944	***0.134	-0.825	***0.134	-0.543	***0.035
Change In Health	1.038	***0.146	1.012	***0.164	0.330	***0.046
Non-Housing Wealth	0.006	0.006	-0.000	0.006	-0.006	***0.002
Income	0.201	***0.04	0.079	*0.041	-0.026	**0.011
Insurance	-0.302	***0.055	-0.522	***0.056	-0.153	***0.015
Number of Children	0.043	***0.010	0.041	***0.010	0.011	***0.003
Age	1.584	***0.204	1.089	***0.208	-0.119	**0.055
Marital Status	-0.128	**0.058	-0.512	***0.057	-0.211	***0.015
Widowed	-0.384	***0.064	-0.469	***0.064	-0.129	***0.017
Northeast Region	-0.155	***0.036	-0.129	***0.014		
Western Region	-0.078	**0.036	-0.096	***0.013		
Midwest Region	-0.079	***0.031	0.020	*0.012		
Black	-0.041	0.040	-0.107	***0.143		
Female	0.447	***0.027	0.249	***0.010		
Years of Schooling	0.088	0.062	-0.724	***0.063	-0.356	***0.016
Lagged Medical Care	1.898	***0.193	0.574	**0.263	-1.838	***0.080
Lagged Consumption	0.100	***0.015	0.091	***0.015	0.015	***0.004
μ_1^m	0.873	***0.010				
μ_2^m	-0.357	***0.012				
ν_t^m	2.362	***0.038				

Note there are three estimates and standard errors for each variable.
All parameter estimates (and standard errors) capture how that variable affects the hazard probability.
The 2nd and 3rd sets of estimates have the variable interacted with γ and γ^2.
γ is a negative valued term that decreases in magnitude in each successive quantile of the distribution of the dependent variable. The estimates for $X\gamma$ and $X\gamma^2$ reflect the effect of given variable on "survival probabilities" changes over the support of the dependent variable.

Table VI: CDE Parameter Estimates for Per-period Consumption

Variables	**X**		**Xγ**		**Xγ^2**	
	Estimate	Std. Err	Estimate	Std. Err	Estimate	Std. Err
Constant	0.213	0.207	-6.903	***0.208	-2.867	***0.053
Health	1.647	***0.140	2.647	***0.140	0.709	***0.036
Change In Health	-0.980	***0.173	-1.745	***0.184	-0.463	***0.050
Non-Housing Wealth	-0.152	***0.003	0.305	***0.004	0.131	***0.001
Income	-0.337	***0.018	1.604	***0.028	0.410	***0.010
Insurance	0.567	***0.056	0.589	***0.055	0.119	***0.014
Number of Children	-0.016	*0.009	-0.080	***0.009	-0.028	***0.003
Age	-2.638	***0.183	1.457	***0.198	1.067	***0.054
Marital Status	0.885	***0.065	1.100	***0.064	0.238	***0.016
Widowed	0.298	***0.077	0.680	***0.075	0.199	***0.019
Northeast Region	-0.092	***0.027	-0.014	0.012		
Western Region	-0.086	***0.025	-0.022	**0.011		
Midwest Region	0.038	0.023	0.041	***0.010		
Black	0.511	***0.036	0.178	***0.016		
Female	-0.173	***0.019	-0.089	***0.008		
Years of Schooling	0.051	***0.061	1.973	***0.065	0.627	***0.017
Lagged Medical Care	0.482	**0.220	2.030	***0.270	0.615	***0.077
Lagged Consumption	0.269	***0.007	0.178	***0.009	0.056	***0.003
μ_1^z	-0.042	***0.014				
μ_2^z	-0.050	***0.010				
ν_t^z	0.051	***0.014				

Note there are three estimates and standard errors for each variable.
All parameter estimates (and standard errors) capture how that variable affects the hazard probability.
The 2nd and 3rd sets of estimates have the variable interacted with γ and γ^2.
γ is a negative valued term that decreases in magnitude in each successive quantile of the distribution of the dependent variable. The estimates for $X\gamma$ and $X\gamma^2$ reflect the effect of given variable on "survival probabilities" changes over the support of the dependent variable.

Table VII: CDE Parameter Estimates for Per-period Health Transition

Variables	X		$X\gamma$		$X\gamma^2$	
	Estimate	Std. Err	Estimate	Std. Err	Estimate	Std. Err
Constant	7.361	***0.663	1.668	**0.746	1.477	***0.213
Lagged Health	-11.445	***0.172	-1.024	***0.146	-0.165	***0.036
Age	6.103	***1.939	2.775	2.183	0.090	0.560
Age Squared	0.055	0.146	-0.058	0.162	0.337	0.443
Change in Health	4.187	***0.595	0.042	0.515	-0.120	0.120
Lagged Medical	3.281	**6.996	-1.389	5.743	-0.947	1.181
Lagged Health*Lagged Medical	-5.278	**2.431	3.926	6.779	-1.987	1.393
Years of Schooling	0.021	***0.007	0.114	***0.008	0.028	***0.002
Years of School*Lagged Medical	0.350	-0.259	-0.021	0.237	-0.021	0.055
Lagged Consumption	1.086	0.055	-0.253	0.048	-0.098	0.056
Northeast Region	0.078	**0.035	0.059	***0.015		
Western Region	-0.175	***0.034	-0.033	0.015		
Midwest Region	0.184	***0.031	0.118	***0.013		
Black	0.686	***0.072	0.268	***0.075		
Female	0.014	0.031	0.138	***0.048		
Lagged Health*Lagged Cons.	-0.288	0.255	0.015	0.232	0.018	0.052
μ_1^H	-1.216	***0.011				
μ_2^H	1.096	***0.011				
ν_t^H	-0.014	0.015				

Note there are three estimates and standard errors for each variable.
All parameter estimates (and standard errors) capture how that variable affects the hazard probability.
The 2nd and 3rd sets of estimates have the variable interacted with γ and γ^2.
γ is a negative valued term that decreases in magnitude in each successive quantile of the distribution of the dependent variable. The estimates for $X\gamma$ and $X\gamma^2$ reflect the effect of given variable on "survival probabilities" changes over the support of the dependent variable.

Table VIII: CDE Parameter Estimates for Initial Health Expression

Variables	**X**		**Xγ**		**Xγ^2**	
	Estimate	Std. Err	Estimate	Std. Err	Estimate	Std. Err
Constant	-2.982	***2.331	2.183	2.489	1.618	**0.642
Age	0.516	0.767	0.096	0.081	0.129	0.201
Age Squared	-0.088	0.615	0.134	0.641	-0.551	1.587
Number of Living Parents	0.134	0.145	0.213	0.154	0.055	0.039
Mothers Age	1.039	*0.542	0.952	*0.511	0.159	0.121
Fathers Age	0.929	**0.475	0.971	**0.454	0.207	*0.109
Years of Schooling	0.095	***0.030	0.143	***0.029	0.021	***0.007
Veteran Status	-0.369	*0.209	-0.369	*0.217	-0.091	*0.054
Insured	-0.818	***0.195	-1.169	***0.202	-0.309	***0.051
Married	0.301	0.233	0.163	0.231	-0.034	0.055
Number of Children	0.069	0.046	0.075	0.047	0.021	*0.011
Northeast Region	0.095	0.093	0.079	**0.039		
Western Region	0.092	0.092	0.093	**0.039		
Midwest Region	0.316	***0.083	0.165	***0.036		
Black	0.091	**0.045	0.053	0.067		
Female	-0.072	**0.031	-0.029	0.031		
Physical Requirements	0.272	***0.075	0.182	***0.034		
Strength Requirements	0.157	0.099	0.017	0.043		
Hazard Exposure	-0.697	*0.409	-0.222	0.180		
$\mu_1^{H_1}$	2.896	***0.029				
$\mu_2^{H_1}$	1.238	***0.022				

Note there are three estimates and standard errors for each variable.
All parameter estimates (and standard errors) capture how that variable affects the hazard probability.
The 2nd and 3rd sets of estimates have the variable interacted with γ and γ^2.
γ is a negative valued term that decreases in magnitude in each successive quantile of the distribution of the dependent variable. The estimates for $X\gamma$ and $X\gamma^2$ reflect the effect of given variable on "survival probabilities" changes over the support of the dependent variable.

Table IX: CDE Parameter Estimates for Initial Medical Care

Variables	**X**		**Xγ**		**Xγ^2**	
	Estimate	Std. Err	Estimate	Std. Err	Estimate	Std. Err
Constant	0.004	3.172	0.112	3.385	-1.480	*0.874
Age	0.174	1.166	-0.033	1.232	-0.377	0.314
Age Squared	-0.096	1.074	0.099	1.120	0.406	2.846
Number of Living Parents	0.215	*0.109	-0.107	**0.044	0.038	0.030
Mothers Age	0.198	0.520	0.373	0.559	0.108	0.144
Fathers Age	0.121	0.481	0.217	0.521	0.067	0.135
Years of Schooling	-0.098	***0.022	-0.140	***0.024	-0.042	***0.006
Veteran Status	0.299	*0.165	0.352	**0.174	0.111	**0.044
Insured	-0.099	0.167	-0.248	0.177	-0.103	**0.046
Married	-0.194	0.162	-0.520	***0.177	-0.176	***0.046
Number of Children	0.027	0.034	0.053	0.037	0.015	*0.009
Northeast Region	-0.047	0.105	-0.002	0.043		
Western Region	0.144	0.093	0.084	**0.038		
Midwest Region	0.121	0.085	0.066	0.048		
Black	0.218	**0.085	0.042	0.120		
Female	-0.126	***0.034	0.109	**0.050		
Physical Requirements	0.167	**0.085	0.033	0.036		
Strength Requirements	0.088	0.111	0.017	0.046		
Hazard Exposure	-0.436	0.455	-0.115	0.189		
$\mu_1^{m_1}$	-0.362	0.037				
$\mu_2^{m_1}$	-0.076	0.036				

Note there are three estimates and standard errors for each variable.
All parameter estimates (and standard errors) capture how that variable affects the hazard probability.
The 2nd and 3rd sets of estimates have the variable interacted with γ and γ^2.
γ is a negative valued term that decreases in magnitude in each successive quantile of the distribution of the dependent variable. The estimates for $X\gamma$ and $X\gamma^2$ reflect the effect of given variable on "survival probabilities" changes over the support of the dependent variable.

Table X: Marginal Effects of Key Variables on Medical Care and Consumption

Variables	Medical Care			Consumption		
	Bottom Quartile	Inter Quartile	Top Quartile	Bottom Quartile	Inter Quartile	Top Quartile
Health	-8.8%	-22.3%	-30.3%	5.5%	3.3%	0.3%
Reference Health	10.5%	14.1%	18.5%	3.8%	4.0%	1.4%
Non-Housing Wealth	0.1%	0.2%	0.1%	1.5%	1.1%	0.7%
Income	-0.1%	-0.2%	-0.4%	29.4%	6.5%	2.8%
Insurance	-3.1%	-2.6%	3.5%	18.2%	7.4%	1.4%
Number of Children	-1.4%	-1.8%	-2.4%	10.4%	0.7%	0.05%
Age	4.1%	2.0%	-5.8%	-10.3%	-14.6%	-10.3%
Marital Status	20.0%	4.6%	-0.7%	18.3%	17.1%	3.7%
Widowed	12.7%	15.5%	12.6%	3.0%	1.8%	0.9%
Black	-31.8%	-23.8%	-9.8%	-2.5%	-21.6%	-16.5%
Female	14.2%	-10.1%	-18.0%	1.7%	2.2%	2.7%
Years of Schooling	-1.0%	-6.8%	-11.5%	4.8%	4.2%	1.5%
Lagged Medical Care	1.1%	1.3%	0.5%	0.1%	0.1%	0.2%
Lagged Consumption	-2.5%	-0.8%	1.1%	1.0%	-1.0%	-1.0%

Table XI: Marginal Effects of Key Variables on Health

Variables	Health		
	Bottom Quartile	Inter Quartile	Top Quartile
Health	4.4%	7.7%	9.1%
Reference Health	4.2%	1.4%	0.8%
Age	-4.1%	-2.3%	-1.4%
Black	-2.4%	-1.8%	-0.7%
Female	12.2%	6.5%	2.2%
Lagged Medical Care	-0.4%	-1.6%	-1.4%
Lagged Consumption	-0.3%	-0.5%	-0.7%
Lagged Health* m_{t-1}	1.2%	2.4%	2.5%
Years of Schooling * m_{t-1}	0.1%	0.0%	-0.1%
Lagged Health * c_{t-1}	0.0%	0.0%	0.0%

Figure 1: Kernel Density of Predicted and Observed Health Index, Medical Care, and Consumption Expenditures Distribution

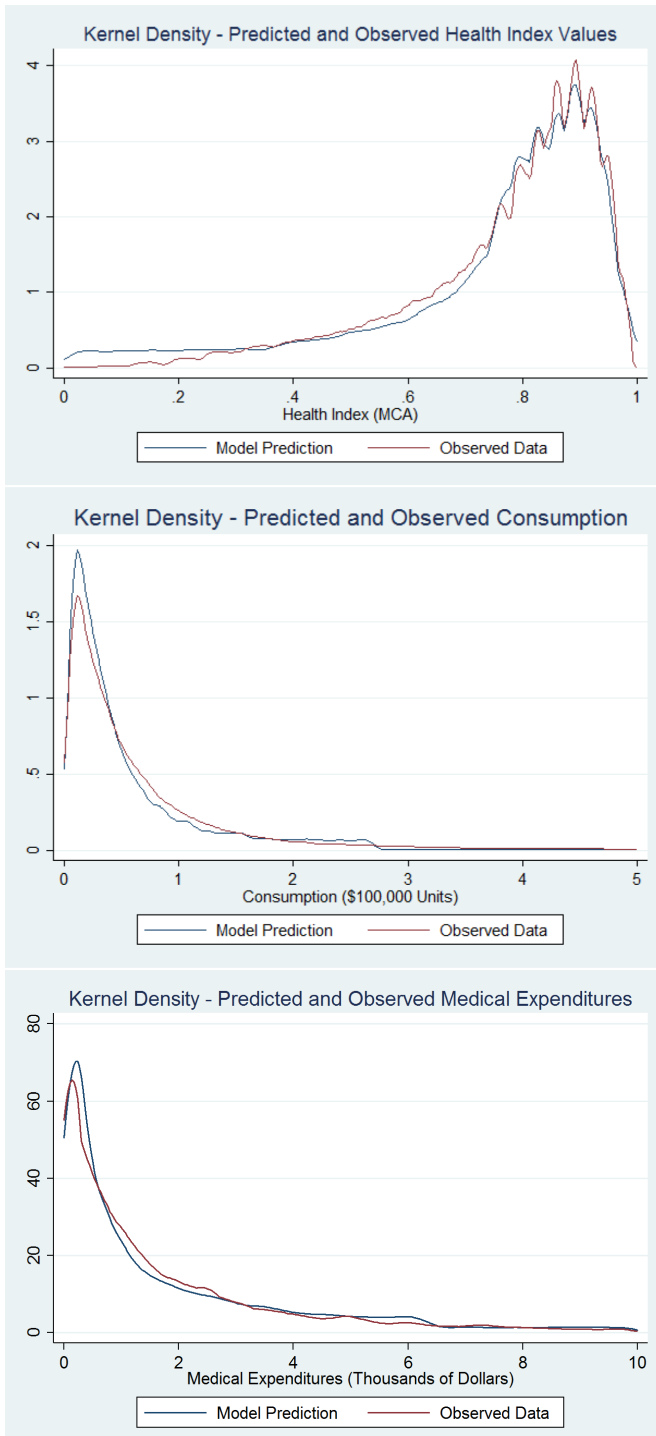

Table XII: Matching Observed Means of the Top 5%

Variable	**Observed Data**	**Preferred Model**	**Grossman**
Age	70.70	**70.77**	73.39
Health	0.636	**0.456**	0.26
Reference Health	0.078	**0.073**	-0.004
Years of Schooling	12.42	**12.13**	11.67
Female	0.635	**0.646**	0.611
Married	0.575	0.487	**0.546**
Income	0.497	0.460	0.432
Lagged Medical Care	0.037	**0.033**	0.055

Numbers in bold indicate they are statistically significantly closer to the values observed in the data by 5%, as determined by two-tailed test for difference in mean.