Modeling the Top Tail of the Medical Care Spending Distribution[1]

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Abstract:

We propose and estimate a dynamic lifecycle model of the joint demands for health and consumption with a focus on explaining the top tail of the medical care spending distribution. Recent work has focused on explaining portfolio choice of financial and other assets over the lifecycle and fit the mean or median of medical care spending. The fact that the top 5% of medical care consumers account for 50% of medical care expenditures motivates the need to model the full distribution of expenditures. The central theoretical hypothesis of this exercise is to determine whether including change in health in the utility function helps to better fit the top tail of the medical care spending distribution. We estimate the joint distribution of medical care spending, non-medical consumption, and the evolution of an individual's health in a dynamic model that allows permanent and time-varying heterogeneity to capture correlation in unobservable factors. Using the RAND Health and Retirement Survey Data, we find that a 10% decline in health from previous average health increases the probability that an individual is in the top 5% of medical care consumers by 40%. Holding the change in health constant but reducing the level of both lagged and contemporaneous health by 10% increases the probability that an individual is in the top 5% of medical care consumers by 80%.

JEL: D11, D91, I1, J17,
Key words: demand for medical care, dynamic stochastic model, health and wealth

[1] The theoretical model in this paper is paper is based on "Health & Wealth: A Dynamic Demand for Medical Care" for which we would like to thank Robert Patrick for his ongoing collaboration. We remain responsible for all errors.

I. Introduction

The skewness of the medical care spending distribution is perhaps its defining and most policy-relevant feature with respect to managing individual and aggregate spending risk and supply-side capacity forecasting. In 2009, the top 1% of the US population consumed nearly 22% of all medical care expenditures, the top 5% consumed nearly 50%, while the bottom 50% consumed barely 3% (Cohn and Yu, 2012). These figures have changed little in the past decade (Yi and Ezzati-Rice, 2005). In addition, there is strong persistence in high medical care spending within individuals over time (French and Jones, 2004; Cohn and Yu, 2012; Kohn and Liu, 2012). Both skewness and persistence are present in both total as well as out-of-pocket (OOP) medical care expenses, even with near universal Medicare coverage in the US. While high spenders and persistent high spenders differ from the general population by age, race, health status, income and insurance status, these observable demographics do not clearly predict who will be a high spender. As noted succinctly by Forget et al. (2008): "Not all of the high-cost users are elderly, nor are most of the elderly high-cost users." Moreover, Webb and Zhivan (2010) find that the uncertainty over catastrophic medical care expenses is reduced very little even after age 65. Similarly, despite the observed positive gradient between health and wealth (Deaton, 2002) those with more wealth are more likely to have high medical care expenditures (Cohn and Yu, 2012). These observations suggest a complex relationship among health, wealth and the demand for medical care of a lifecycle.

Extant economic models have trouble explaining the why individuals demand so much medical care even when survival probabilities are low. In fact, such investment appears contradictory from a purely economic perspective: why invest in a capital good such as health if a high probability of death due to either old age or acute illness reduces the likelihood of re-cooping the investment? Much theoretical and empirical literature is based on the seminal Grossman (1972) human capital model. Grossman concludes that as health declines the marginal cost of health investment increases causing individuals to demand less health and ultimately "choose death"(Grossman, 1972, p. 240). However, this conclusion is driven by the multiplicative functional form used for health depreciation (a rate of depreciation multiplied by stock of health) which does not accord with health shocks to the relatively young and healthy or the rapid decline in health that we observe at the end of life when even a large rate of depreciation multiplied by a small stock of health results in a small change in health.[2] Moreover, the Grossman model does not posit a testable hypothesis about how the demand for medical care changes over the lifecycle. Rather, Grossman concludes that "…even though health capital falls over the life cycle, gross investment might increase, remain constant or decrease" (Grossman, 1972, p. 238).

Nonetheless, empirical estimates of the demand for medical care have become increasingly sophisticated in reflecting the skewed distribution of demand. Reduced form estimates have evolved from the two-part model to capture the high frequency of zero use and long right tails with increasingly complex distributions and mixing methods for modeling latent unobservable selection characteristics (Cameron and Trivedi, 1986, Pohlmeier and Uhlrich, 1995, Deb and Trivedi,1997, Gurmu, 1997, Cameron and Johansson, 1997, and recently Creel and Farrell, 2005, have directly compared these models).

Structural models have also become increasingly more complex and adept at fitting medical care demand data. In part due to advances in computer power, Discrete Choice Dynamic Programming (DCDP) and microsimulation methods have evolved to include multiple state spaces and forms of static and time-varying heterogeneity (Yang et. al., 2009; Khwaja, 2010, are two recent DCDP examples based on the Grossman model; Edwards, 2008; Hall and Jones, 2007; Yogo, 2009; Hugonnier et al., 2013 all model the joint demands for health and wealth over the lifecycle; Zuccelli, Jones and Rice, 2012 review microsimulation methods). However, this work has not focused on modeling participation in the top tail of the medical care demand distribution nor has it offered an economic explanation for what drives decision making in the top tail. Rather, much of this work has focused on retirement and savings decisions and fit medical care demand to the mean or median of the spending distribution. Furthermore, Zuccelli, Jones and Rice (2012) note that the output of microsimulation models rely on the particular assumptions used, and that additional theoretical work is necessary to determine the "appropriate theoretical framework to define agents' dynamic optimizing behavior" (p. 16).

French and Jones (2004) explicitly model both the distribution and dynamics of medical care spending. However, they take a purely statistical approach. While their examination of the

[2] Most models that extend Grossman (1972), maintain this functional form assumption including Ehrlich and Chuma (1990); Dardanoni and Wagstaff (1990); Wagstaff (1993); Liljas (1998); Ehrlich (2000); Galama (2011). A recent review of the theoretical limitations of the Grossman model does not mention the multiplicative functional form specification or the change in health (Hren, 2012).

time series properties of medical care demand resulting in a data generating process consisting of white noise plus a persistent AR(1) process captures catastrophic health spending risk, it does not offer insights into the decision-making process driving the agents to demand high amounts of medical care.

The goal of the present work is to go back to economic first principles to specify a utility maximization model that offers a testable hypothesis that can explain observed demand behavior of the top tail of the spending distribution, test this hypothesis, and simulate the medical care spending distribution with a focus on the top tail. Our theoretical approach builds on the Grossman model and the Ehrlich and Chuma (1990) and Galama (2011) extensions. Our theoretical innovations are to include the dynamic change in health as an element in utility and generalize the health production function. These modeling changes result in a testable economic hypothesis as to why individuals would be in the top 5% of medical care spending. Our econometric estimation approach is different than the most recent work estimating joint demands for medical care and consumption that uses calibrated simulations. To our knowledge, we are the first to employ a Conditional Density Estimator (CDE) with an eight-equation discrete factor random effects likelihood model to jointly estimate medical care spending, other consumption and the time path of health, including the probability of death, along with initial conditions for health and medical care spending and consumption. This estimation strategy is particularly well suited to our focus on estimating the top tail rather than merely the conditional mean of the medical care spending distribution. Our empirical estimates provide support for the theoretical hypothesis that incorporating the change in health can help to predict the top tail of medical care spending. We also find that whether health and consumption are complements or substitutes depends on the magnitude and sign of the change in health. This finding on the cross-partial of health and consumption may help to reconcile conflicting findings in the literature.

The paper proceeds as follows: Section II briefly specifies the theoretical model and states the hypotheses to be tested. Section III discusses the estimation strategy. Section IV describes the data including our proxy for the unobservable state of health. Section V presents results and a discussion of the implications, and Section VI summarizes and concludes with directions for future research. Appendix A lists the notation, and Appendix B describes the continuous health index used for the estimation.

II. Theoretical model

This model is fully developed in Kohn and Patrick (2012, in revision).[3] Briefly, the model extends the Grossman human capital model in two ways. First, the change in health is included as a state variable in the utility function. The intuition is that individuals are able to adapt to small declines in their health (Groot, 2000) but larger changes decrease the utility from any level of health and consumption. Second, the health transition function is generalized to allow health to affect the productivity of medical care and health depreciation to evolve as a periodic impairment rather than a multiplicative rate. The former is consistent with the observation that health outcomes are impaired by comorbidities: the lower (higher) the health, the worse (better) the prognosis from any medical intervention. Periodic health impairment, which is modeled as a function of age and may easily be extended to a function of health,[4] is consistent with the observation that individuals' health declines more rapidly at the end of life (like a cliff), rather than more gradually (like a ski-slope) as implied by the multiplicative specification.[5] The model notation is as follows with a list of the notational definitions in Appendix A.

Individuals choose consumption, *z*, medical care, *m*, and the terminal time of death, *T,* to maximize lifetime utility from consumption, health, H, and the change in health, A[6]:

$$LU \equiv \int_0^T e^{-rt} U\left[z(t), H(t), A(t)\right] dt \tag{1}$$

subject to the transition equations for health, the change in health, and wealth, R:

$$\dot{H} = \alpha\left(t, m(t), H(t), \delta(t)\right) \tag{2}$$

$$\dot{A} = \ddot{H} = \dot{\alpha} \tag{3}$$

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[3] A prior version of this theoretical model that had a different specification for the change in health was in Kohn, 2009.

[4] In the present model depreciation is a deterministic function of time and not the state of health. Prior specifications included health as an element in the depreciation function, but the result was more cumbersome notation without any additional theoretical insights. Rather, the present model includes health as an element in health investment which does yield new insights.

[5] This specification of depreciation as a periodic impairment rather than a rate is also consistent with current accounting for intangible assets. See FASB #142.

[6] Our time separable lifetime utility is fairly standard in the literature. However, we acknowledge the limitations of this model in the presence of an uncertain and endogenous time horizon described in Hugonnier et al., 2013. First, while our empirical specification includes uncertain health shocks, our theoretical model is not at this time stochastic. Prior work (available upon request) confirmed the standard result in the literature that stochastic health shocks result in precautionary health and wealth reserves, but do not otherwise alter the key implications of the model four our present focus. Second, our empirical strategy does not at this time rely on specific functional forms for utility.

$$\dot{R} = rR(t) + w(H(t)) - P^m(t)m(t) - P^z(t)z(t) \tag{4}$$

and subject to the endpoint conditions:

$$H(0) = H_0 > H_{\min},\ H(T) = H_{\min} \tag{5}$$

$$A(0) \text{ free, } \mathrm{A}(T) < 0 \tag{6}$$

$$R(0) = R_0 \geq 0,\ R(T) \geq 0 \tag{7}$$

$$T \leq T_{\max}. \tag{8}$$

Let z^* and m^* be the optimal controls, defined on the interval $\left[0,T^*\right]$, that solve the problem.

Then there exist continuous adjoint functions $\lambda^H(t),\ \lambda^R(t),$ and $\lambda^A(t),$[7] such that for all $t \in \left[0,T^*\right],\ z^*$ and m^* maximize the Hamiltonian value function denoted V:

$$\begin{aligned} V = e^{-rt}U\big(z(t),H(t),A(t)\big) + \lambda^H\alpha\big(t,m(t),H(t),\delta(t)\big) \\ + \lambda^A\dot{\alpha}\big(t,m(t),H(t),\delta(t)\big) + \lambda^R\left[rR(t) + w(H(t)) - P^m(t)m(t) - P^z(t)z(t)\right] \end{aligned} \tag{9}$$

Necessary conditions include the following.

$$\dot{\lambda}^H = -\frac{\partial V}{\partial H} - \left[e^{-rt}U_H + \lambda^H\alpha_H + \lambda^A\dot{\alpha}_H + \lambda^R w_H\right] \tag{10}$$

$$\dot{\lambda}^A = -\frac{\partial V}{\partial A} = -e^{-rt}U_A \tag{11}$$

$$\dot{\lambda}^R = -\frac{\partial V}{\partial R} = -\lambda^R r, \tag{12}$$

except at points of discontinuity of z^* and m^*. Given $z^* > 0$ and $m^* > 0$,

$$\frac{\partial V}{\partial m} = \lambda^H\alpha_m + \lambda^A\dot{\alpha}_m - \lambda^R P^m = 0, \tag{13}$$

and

$$\frac{\partial V}{\partial z} = e^{-rt}U_z - \lambda^R P^z = 0. \tag{14}$$

Given $T \leq T^{\max}$,

$$V(T^*) \geq 0;\ T_{\max} - T^* \geq 0; \text{ and } V(T^*)(T_{\max} - T^*) = 0. \tag{15}$$

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[7] The superscripts on λ denote the multiplier for health, H, wealth, R, and the change in health, A, respectively.

The terminal condition $H(T) = H_{\min}$ implies no transversality condition on $\lambda^H(T^*)$. The terminal condition $A(T) < 0$ implies the transversality condition:

$$\lambda^A(T) < 0 \tag{16}$$

The terminal condition $R(T) \geq 0$ implies the transversality condition:

$$\lambda^R(T^*) \geq 0 \; (= 0 \text{ if } R(T^*) > 0) \tag{17}$$

For notational ease, we drop the * and (t) notation below except where necessary for clarity or to indicate the initial (0) or terminal (T) time. Testable hypotheses associated with the model are derived from the equilibrium demand for health and time paths for medical care and consumption which are based on the simultaneous solution of the necessary conditions above. Full derivations of these and the additional testable hypotheses associated with full comparative dynamics of the model are available in Kohn and Patrick (2012).

In much of the literature the equilibrium condition (18)~~(18)~~ is interpreted as the equilibrium demand for health, but following Galama (2011) it can also be viewed as the equilibrium demand for health investment, or medical care.[8] In either case, the equilibrium condition sets the marginal benefits from health on the left hand side equal to the marginal costs on the right:

$$\frac{U_H}{\lambda^R(T)} + w_H = g\left[r - \alpha_H - \tilde{g}\right] \tag{18}$$

Following Ehrlich and Chuma (1999) $g = \dfrac{\lambda^H}{\lambda^R}$, the cost of health capital, with $\tilde{g}$ indicating the percent change in cost. The critical difference between this equilibrium demand specification and Grossman's (see 1972, equation A13) is in the α_H term, which is the marginal productivity of health production with respect to health. This term is subtracted from the cost of health capital as a result of modeling health production as a function of health. Note that depreciation, now modeled as a periodic impairment rather than a rate, is no longer added to the cost of health capital. Rather than the cost of health capital increasing by the rate of depreciation, it decreases at the marginal rate that health contributes to the future change in health. Intuitively, rather than reflect the wasting away of a resource, this formulation credits individuals with the forward-

[8] We follow the majority of the literature in our focus on medical care to improve health while acknowledging that some recent literature has begun to include "healthy leisure" to improve health (DiNardi et al., 2010; Pelgrin and StAmour, 2014). We leave incorporating healthy (unhealthy) behaviors to future work.

looking benefit of health to reduce the future decline in health. Again, this perspective is consistent with the observed effect of comorbidities on the productivity of medical care as well as the ability of a healthy body to heal thyself even in the absence of medical care.

The critical implication of this equilibrium demand for health is that, on the margin, the benefit of an incremental additional amount of health to future health is greater the lower level of health. Thus, the model predicts that as health declines, the marginal cost of health capital declines rather than increases. At the same time, the marginal benefit from health increases. This causes *an inevitable disequilibrium* that individuals can only bring back into balance with increasing amounts of medical care. This equilibrium condition, in contrast to Grossman's, unambiguously predicts that a decline in health will cause an increase in medical care demand. The key inference is: the greater the decline in health, the greater the disequilibrium, and therefore the greater the demand for medical care regardless of the state of health. This suggests an explanation consistent with utility maximization for both older, sicker individuals to invest in health when survival and longevity prospects may be poor as well as younger relatively healthy individuals to have significant investments even when "need" may not be apparent using static measures of health.

The time path for medical care demand is derived from the necessary condition (13)~~(13)~~ with the signs from the necessary and/or sufficiency conditions of the model.

$$\dot{m} = \frac{\overset{+}{\lambda^H}\,\overset{+}{\alpha_m} - \overset{+}{\lambda^R}\,\overset{+}{P^m}}{-\overset{+/-}{\lambda^A}\,\overset{-}{\alpha_{mm}}} + \frac{\left(\overset{+}{\alpha_{mH}}\,\overset{+/-}{\dot{H}} + \overset{+}{\alpha_{mt}}\right)}{-\overset{-}{\alpha_{mm}}} \tag{19}$$

Under the typical Grossman assumption that utility is not relative to the change in health (making $\lambda^A = 0$) equation (19)~~(19)~~ is undefined. An undefined time path for medical care demand is consistent with Grossman's ambiguous conclusion that the demand for medical care may increase, decrease or stay the same as health declines. Furthermore, if medical care productivity is independent of time and the state of health $(\alpha_{mH} = \alpha_{mt} = 0)$ the second term is zero suggesting level demand for medical care over the lifecycle.

By contrast, under the specified model there are several scenarios that would support the observed positive time path, though the time path cannot be signed unambiguously. The first term of the time path is positive so long as the marginal benefit from medical care $(\lambda^H \alpha_m)$

exceeds the marginal cost $(\lambda^R P^m)$ consistent with standard economic theory. What is notable is that this difference between costs and benefits is relative to the value of the change in health which is positive but declines unambiguously over the lifecycle ($\dot{\lambda}^A < 0$, see necessary condition (12)~~(12)~~). Therefore, if the change in health is relevant to utility then the demand for medical care will increase over the lifecycle all else equal. In other words, for a given economic benefit from medical care, the demand for medical care will be higher the closer the time to death.[9]

Second, all three costate variables, λ^H, λ^A and λ^R are present in the time path of medical care demand. This suggests that the time path of demand is a function of all of the model parameters including consumption. This link between the demands for medical care and consumption is also apparent in the time path of consumption which is derived from the necessary condition (14)~~(14)~~:

$$\dot{z} = \frac{\left[U_{zH}\dot{H} + U_{zA}\left(\alpha_t + \alpha_m \dot{m} + \alpha_H \dot{H} + \alpha_\delta \dot{\delta}\right)\right]}{-U_{zz}} \tag{20}$$

The time path of medical care demand, $\dot{m}$, is an element of the time path of consumption. Thus, the model suggests that the demands for medical care and other consumption should be estimated jointly. Models that estimate the demand for medical care without incorporating the simultaneous demand for consumption implicitly assume independence between the demands which is not supported by the underlying theory.[10]

Thus, the hypothesis associated with the model that will be tested in this paper is:

H1: *The greater the decline in health the greater the demand for medical care independent of the state of health.*

Two testable assumptions:

A1: *The higher the level of lagged, the smaller the effect of a decline in health on medical care expenditures* (due to the increased productivity of medical care when health is higher); and

A2: *The demands for medical care and other consumption are not separable*.

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[9] The transversality condition for λ^A requires the costate to be negative at the terminal time. Thus, at some point prior to death the costate crosses the zero boundary making the time path for medical care demand undefined. This suggests interesting implications for end of life care and a theoretical explanation for the time-to-death bias observed in the literature by Sterns and Norton (2004). .

[10] Extant empirical tests of the Grossman model typically use a pure investment formulation to avoid joint estimation. Wagstaff (1986) noted that the pure consumption model does require joint estimation of the demands for health and other consumption due to the cross price effect of a wage change on the marginal cost of consumption. However, Wagstaff further notes that data limitations prevent such joint estimation.

Whether these demands are complements or substitutes is not assumed by the model but is an empirical question on which the literature has not yet reached a consensus (see Edwards, 2008 for a recent review of empirical cross-partial findings). It may be that health and consumption have different cross-partial effects on utility at different points in the lifecycle and different points on the health distribution.

III. Econometric Specification and Estimating Strategy

We jointly estimate the demands for consumption, medical care, and the evolution of health in a framework that permits correlation between the errors for each expression and serial correlation in the errors for each expression over time. Our specification captures the dynamics of how health affects both the decision to consume medical care and, through the budget constraint, the decision on other consumption, and how these decisions in turn affect health in future periods. Our estimation strategy is chosen with an eye to testing the theoretical hypotheses of the model and simulating the full distribution of medical care spending rather than merely estimating mean or median effects.

A. Timing assumptions

To translate the continuous-time theoretical model to the discrete time empirical implementation, we make the following assumptions about timing. We assume that the individual enters each discrete period knowing her exogenous characteristics, $\mathbf{X}_t$, including age, gender, marital status, education, etc., as well has her endogenous health state H_t and all past realizations of health and medical care consumption $[H_{t-k}, m_{t-k}] \forall k \in \{1, \ldots, t\}$. These past realizations of health reflect the new change in health state in the theoretical specification, A_t. To be clear, it is an innovation of the theoretical model to suggest that individuals make decisions relative to their health history, not just their current-period health. The central theoretical hypothesis of this exercise is to determine whether adding the change in health helps to better fit the top tail of the medical care spending distribution. Knowing their demographics, current and past health as well as the functional forms (unknown to the econometrician) for the wealth and health production functions, the individual then chooses medical care, consumption and savings to maximize lifetime utility. Since the change in health state is in the utility function, not just in the health production function, the change in health is included in both the demand for consumption and the demand for medical care equations.[11] Thus, the joint demands for consumption and medical care can be expressed as follows:

$$z_t^* = z(H_t, \Delta H_t, m_{t-1}, z_{t-1}, \mathbf{X_t}, \epsilon_t^z)$$
$$m_t^* = m(H_t, \Delta H_t, m_{t-1}, z_{t-1}, \mathbf{X_t}, \epsilon_t^m) \tag{21}$$

where $\Delta H = H_t - \frac{1}{p}\sum_{i=1}^{p} H_{t-i}$, and p is the number of periods that define the individual's "habitual" level of health. In other words, the change in health, ΔH, is the deviation from the average health of the prior p observations. These choices then affect health at the start of the next period:

$$H_{t+1} = H(H_t, m_t, z_t, \mathbf{X_t}, \epsilon_t^H) \tag{22}$$

To maintain a reasonably parsimonious model in order to focus 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 elements included in the literature.[12] 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.[13] We include variables on employment, insurance status, age and income in the model.

B. Identification

The empirical identification of this model comes through three sources. First, we exclude lagged consumption and health history from the health transition expression. Our theoretical model implies that the change in health from some 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

[11] Other papers that include health dynamics incorporate past health in a survival equation, but not directly in the demands for medical care and consumption.
[12] See Pelgrin and St-Amour (2014) Table 3 for an excellent summary of the major modeling choices in much of the literature.
[13] We are considering how to model labor force participation for future specifications.

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 non-medical goods, but not affect the health transition.

Second, the model is identified through the timing of the model. However, to appeal to the timing assumption, we must specify endogenous initial conditions for the health state and initial demand for medical and non-medical goods. Because we empirically model "change in health" as the difference between current period health and the level of health to which the individual is accustomed, we must define initial conditions for health in each period that will inform the first choice. We also require initial conditions for the first observed consumption of medical and non-medical goods. Setting *p=2*, we write:

$$\begin{aligned} H_1 &= H_1^i(\mathbf{X_1}, \mathbf{Z_1}) \\ H_2 &= H_2^i(\mathbf{X_2}, \mathbf{Z_2}) \\ m_2 &= m^i(\mathbf{X_1}, \mathbf{Z_1}) \\ z_2 &= z^i(\mathbf{X_1}, \mathbf{Z_1}) \end{aligned} \tag{23}$$

where $\boldsymbol{Z_t}$ is a set of exclusion restrictions for our initial conditions. Our exclusions restrictions are 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 the data section. See Table 1 for the variables in each equation, which clearly displays the exclusion restrictions of the model. Finally, some identification is attained by the non-linearity of all expressions in the model.

C. Conditional Density Estimation

For each expression in equations (21) , (22), and (23), we employ Conditional Density Estimation (CDE) to jointly estimate the distribution of medical care expenses, non-medical consumption, health transition, and initial conditions (Gilleskie and Mroz, 2004). For our purposes, CDE provides three advantages. First, CDE does not require parametric assumptions on the distribution of the error terms. This permits us to flexibly model left or right skewed distributions (recall that both medical care spending and consumption are left skewed while health is right skewed). Second, because we estimate the conditional density of the variable of interest, we can match any moment of the distribution of that variable, not just the conditional mean or conditional median. 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 that change in health may have a stronger effect in the top tail of the distribution of medical care consumption than at the mean. Given our research question to fit the top tail of the medical care spending distribution, these features of our CDE are critical.

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 a *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 is given by:

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

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

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

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:

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

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:

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

As suggested by Gilleskie and Mroz (2004), we use logit probabilities for the hazard 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 (21)-(23) and for each cell $k \in \{1, . . ., K\}$, we can write:

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

With some abuse of notation, X^j is inclusive of all variables in expression *j*. Thus:

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

Which are the hazard probabilities used to estimate the conditional density of our outcomes of interest.

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 with a step function (Heckman and Singer, 1984; Mroz, 1999). 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.

We include a time-invariant, permanent unobserved heterogeneity component that may influence an individual's joint choice of medical care, non-medical consumption, and 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. The second component of heterogeneity is meant to capture changes 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 (21) and (22) into three components:

$$\varepsilon_t^j = \mu^j + v_t^j + e_t^j \quad \forall j \in z, m, H \tag{24}$$

where μ^j captures the permanent heterogeneity for each expression, v_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. The errors in the expressions for the initial conditions are similarly decomposed into permanent heterogeneity and a serially uncorrelated i.i.d. Type-1 extreme value error. 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 and 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 demanded and non-medical consumption;. The probability of death is estimated with a logit as death is a binary outcome.[14] Combining these expressions into a likelihood function results in the estimating equation below:

$$L_i\left(\Theta,\psi,\pi\right) = \sum_{k=1}^{K} \pi_k \left\{ \begin{array}{l} \prod_{j_{f=1}}^{J_f} \Pr\left(H_1 = j_f \,\middle|\, \mu_k^F\right)^{1(H_1=j_f)} \prod_{j_{s=1}}^{J_s} \Pr\left(H_2 = j_s \,\middle|\, \mu_k^F\right)^{1(H_2=j_s)} \prod_{j_{s=1}}^{J_s} \Pr\left(m_1 = j_m \,\middle|\, \mu_k^m\right)^{1(m_1=j_m)} \\ \times \prod_{t=2}^{T_i} \sum_{l=1}^{L} \psi_l \left[\begin{array}{l} \prod_{j_{m=1}}^{J_m} \Pr\left(m_t = j_m \,\middle|\, \mu_k^m, v_{lt}^m\right)^{1(m_t=j_m)} \prod_{j_{z=1}}^{J_z} \Pr\left(z_t = j_z \,\middle|\, \mu_k^z, v_{lt}^z\right)^{1(z_t=j_z)} \\ \prod_{j_{h=1}}^{J_h} \Pr\left(H_{t+1} = j_h \,\middle|\, \mu_k^H, v_{lt}^H\right)^{1(H_{t+1}=j_h)} \\ \Pr\left(death \,\middle|\, H_t, m_t, z_t, \mu_k^D, v_{lt}^D\right)^{\mathbf{1}(death)} \left(1-\Pr\right)\left(death \,\middle|\, H_t, m_t, z_t, \mu_k^D, v_{lt}^D\right)^{\mathbf{1}(1-death)} \end{array} \right] \end{array} \right\} \tag{25}$$

where Θ is the vector of parameters to be estimated within the model, ψ_l are the mixing parameters for the time-varying heterogeneity, π_k are the mixing parameters for the permanent heterogeneity. K represents the number of mass points for the permanent heterogeneity, L

[14] Permanent and time varying heterogeneity also enter the probability for death.

represents the number of mass points for the time-varying heterogeneity; and t indexes the waves in the data for each individual. The terminal time T_i is indexed for each individual because some individuals die during the sample period. J_f, J_s, J_m, J_z are the number of cells for the conditional density estimation for the initial health state, second health state, medical care expenditures, and consumption respectively.

IV. Data

We estimate the model using the RAND files of the Health and Retirement Study (HRS), a longitudinal panel survey of individuals 50 years old and over. The HRS contains information on individual's wealth, income, consumption, occupational history, family state, chronic health conditions, difficulties with activities of daily living, and expenditures on medical care. The HRS was conducted biennially 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, two features of the HRS create limitations for testing the theoretical model. First, as it excludes those under age 50, we are unable to fully capture the age distribution of the top 5% of medical care consumers, of which nearly 40% were younger than 55 in 2009 (Schoenman, 2012). Second, although the survey is biennial, respondents are asked to recall information only the last 12 months.

In order to estimate the model with valid initial conditions, we must restrict the sample to those who are observed for at least three periods. With this restriction, we have a sample of 173,312 observations comprised of 25,872 individuals.[15] Summary statistics of our working sample are available in Table 2.

We jointly model four outcomes of interest: medical care expenditures, aggregate consumption expenditures, the evolution of the health state, and probability of death. We include the probability of death because the terminal time is endogenous in the theoretical model, and prior empirical work has suggested that medical care spending is higher in the year prior to death (Sterns and Norton, 2004). RAND HRS includes two measures of total medical care expenditures: out-of-pocket medical care expenditures and total medical care expenditures. We

[15] We use dummy indicators for missing responses, which are primarily variables only in the initial conditions equations (veterans' status, occupational requirements) and insurance status in Wave 1. Eliminating all observations with missing response would reduce the sample size by more than half.

chose out-of-pocket medical care expenditures for two reasons. First, because we are concerned with the individual's optimization problem, the out-of-pocket expense reflects the cost to the individual. Second, total medical expenditures are documented only for the first six waves, so using total medial expenditures would halve the number of observations. In constructing the variable for the health state, we utilized the HRS' rich data on objective and subjective measures of health (presence of chronic conditions, ADL's, mental health, and self-reported health status). To keep the model tractable, we employ Multiple Correspondence Analysis (MCA) to rotate the multiple measures of health into a single continuous variable.[16] See Appendix B for details on the index variables and weights. The additional benefit of our health index is that it purges unobservable cut-point and adaptation heterogeneity associated with the most commonly used self-assessed health variable (see Contoyannis et al., 2004 and Kohn, 2012 for further discussion of the limitations of self-assessed health). We then calculate change in health based upon this calculated health variable rather than using change variables directly from HRS. We calculate consumption of the aggregate good by subtracting change in non-housing financial wealth and out-of-pocket medical expenses from income.[17] Death is recorded in the data. Approximately 16% of the sample dies during the sample period.

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, 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.[18] Both of these results are intuitive (most people are fairly healthy and medical care expenditures and non-medical consumption are driven by right-tailed income and wealth distributions) but underscore the importance of modeling the distribution beyond estimating the conditional mean.

[16] For data reduction purposes, MCA is used for transforming 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.
[17] 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. The median person in our sample has non-housing financial wealth of $10,500, and $250,000 at the 90th percentile. Except for the upper tail of the wealth distribution, unobserved capital gains are a minimal concern in calculating consumption.
[18] Future versions of this paper will include kernel densities.

For identification we need valid exclusion restrictions for our initial conditions. We briefly mention four variables (veteran status, strength required at work, environmental hazard exposure at work, and physical demands from work) above that should affect the individual's health and consumption history up to the first period of observation, but should not affect subsequent decisions conditional on the initial state.[19] The individual's occupational strength, occupational environmental hazard, and occupational demands are calculated by multiplying these occupational indices by the reported tenure in their reported occupation. The individuals reported tenure in their reported longest held occupation serves as a dosage effect.

V. Results

A. Estimates and Marginal Effects

Preliminary parameter estimates from the joint CDE estimation are in tables 2-7. We have estimated the model as specified above with three mass points in both the permanent and time-varying heterogeneity. One motivation for using CDE is to capture the skewed distributions of health, consumption, and medical care. Figures 1-3 illustrate this skewness. Since the estimates are for parameters in non-linear hazard probabilities they are not directly interpretable without numerical simulation. We therefore report the key preliminary static marginal effects below and Table 8 reports marginal effects for all variables of interest. Recall that one benefit of using CDE is that we can report marginal effects at different points of the support of the dependent variable. We report three: one for the effect of the explanatory variable in the lowest quartile of the dependent variable, 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. Note that these effects vary over the support of the *dependent* variable, not the explanatory

[19] Veteran status is in the HRS data. The indices of occupational demands were constructed using reported occupation in the HRS and the second supplement to the 1991 Dictionary of Occupational Titles (DOT).[19] The DOT contains information on 12,686 "occupations," each of which is mapped into a 1980 SOC code. For each occupation, the DOC contains a five category measure of requisite strength, eleven variables of frequency with which particular physical activities were required (stooping, climbing stairs) and seventeen variables on exposure to environmental hazards (extreme noise, heat, corrosive materials, toxins, etc.) We form our occupational exposure variables as follows. First, we sum the frequencies of each exposure variable and average over all DOT occupations for each SOC code. We then use 1990 CPS weights to average over the SOC codes for each of the 17 broad Census Occupation Codes as reported in HRS.

variable.[20] In the case of a binary variable, marginal effects are calculated by taking expectations with the indicator turned on and off and differencing. For continuous variables (e.g., income), marginal effects are calculated by taking expected expenditures at median levels of explanatory variables and subsequently calculating expectations with the explanatory variable increased by 10% from the median.

For interpretation, consider the marginal effect of having insurance on medical care consumption – left column of Table 8. The marginal effect of having insurance on out-of-pocket medical care expenditures is negative (-3.1%) 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%) and *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 – or, those who spend the most on care may also face the most binding budget constraint. To take another example, the effect of education is negative across the distribution, consistent with education increasing health productivity. The magnitude of the marginal effect of education increases from -1.0% at the bottom quartile to -11.5% 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. The full list of marginal effects is available in Table 8.

B. Tests of the theoretical hypotheses

The critical finding is that controlling for contemporaneous health, the change in health from previous two period (four year average) does significantly affect the demand for medical care. Using the same simulation process as used for Table 8, a 10% decline in health results in a 22% increase in the probability that an individual is in the top 5% of medical care consumers, and increases expected medical care consumption by 18%. This result supports hypothesis H1, and all parameters are significant at the 1% level. For perspective, if we decrease contemporaneous health *and* previous health by 10% (thereby holding change-in-health constant) the probability that in individual is observed in the top 5% of the medical care expenditures

[20] Note that marginal effects can vary over the explanatory variable as well, but only insofar as changes in the explanatory variable affect the probability that we observe the dependent variable in different areas of its support. This is due to non-linearities in the hazard probabilities.

distribution increases by 180%.[21] Thus, health dynamics compound the effect of poor health on high medical care demand. The model also accurately captures the difference in health state *and* change-in-health from habitual levels between individuals in and out of the top 5% of medical care consumption. In the observed data, individuals in the top 5% of medical care consumers exhibit an average health index of 0.635, compared to a mean of 0.774 for those outside the top 5%. The model predicts a health index of 0.594 for those in the top 5% of medical care consumers vs. a mean of 0.760 for those outside of top 5%. In the HRS individuals in the top 5% of medical care consumers exhibit a -0.078 decline in health from their trailing two-period average; individuals outside the top 5% only report a -0.024 change in health. The model predicts that individuals in (outside of) the top 5% of medical care consumers report a change in health of -0.082 (-0.022).

Second, we find that the demands for medical care and consumption are not separable. The estimated parameters for the permanent and time-varying heterogeneity that affect both medical care demand and aggregate consumption are significant at the 1% level. This result supports secondary hypothesis A2 and is consistent with recent literature that has modeled the joint demands for medical care and other consumption (Yogo, 2009; DiNardi, French and Jones, 2010; Hugonnier et al., 2013).

Third, we find that a 10% decrease in health leads to a 4% reduction in consumption, but that a 10% increase in current and previous health leads to a 3.3% 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.[22] Most of the individuals in the HRS are very near or past retirement. While it follows that a positive change in health should predict lower consumption (and greater saving) due to increased expected longevity, the positive effect of level health on consumption, we interpret as complementarity. This finding, which we will explore further in ongoing research, may shed light on the contradictory findings about the relationship between health and consumption in the literature. Edwards (2008) and DiNardi, French and Jones (2010) find a

[21] Marginal effects are calculated using the simulation method as described in V.B.~~,~~ We simulate the model using the original data and estimated parameters. We then alter the variable of interest, re-simulate the model, and compare the results.

[22] Although in this version of the model we do not model labor force participation and wages. It is possible that this effect is being driven by the endogeneity of income with respect to health.

negative cross-partial between health and consumption suggesting the two are substitutes while Finklestein et al. (2013) and Viscusi and Evans (1990) find a positive cross-partial suggesting complementarity. Our results suggest that whether health and consumption are complements or substitutes depends not on the absolute level of health, but on the relative change in health and is consistent with the assumption that individuals can better adapt to small rather than large changes in their health.

C. Simulations

When simulating the model, we replicate each observation in the data 80 times. 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.

First, we test hypothesis A1: The greater the level of lagged health, the smaller the effect a decline in health will have on medical care expenditures. To test hypothesis A1, we exogenously increase and decrease individuals' initial health states by 10 percentage points. We then simulate the model using the estimated parameters and compare the simulated marginal effect of change in health on medical care expenditures under the different initial health states. We find that the marginal effect of a decline in health on medical care expenditures is 6% larger (smaller) when we reduce (increase) initial health by 10% points.

From a policy perspective, the primary contribution of our model and empirics is improved prediction of dynamic health investment and matching the top 5% 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. At the conditional mean, the covariates available to us explain 6% of the variation in medical care consumption. Using 6% as a bench mark, our model represents improvement if it generates a match rate that is 6% greater than random.

Simulating the model as described above, our model generates a 12.5% match rate between predicted and observed individuals in the top 5% of medical care consumers. We also have estimated this model under a specification consistent with the seminal Grossman model, one which does not include habit-in-health nor lagged medical care or aggregate consumption. This specification generates an 8.5% match rate of predicted and observed individuals in the top 5% of medical care. Our model outperforms the Grossman-consistent model in matching by 47%. One of the primary motivations for including change in health from habitual levels in the utility function is to help explain why individuals who are in relatively good health may still be among in the top 5% of medical care consumers. To gauge the model's effectiveness in capturing this phenomenon, we compare the summary statistics for individuals predicted to fall in the top 5% of medical consumers by our model and the Grossman model to the observed data. These summary statistics are exhibited in the Table 9.

Conditional density estimation has the advantage of fitting moments of the distribution of an outcome beyond the conditional mean. To gauge our model's effectiveness in fitting the full distribution of medical care consumption, we create an indicator variable for whether an individuals' predicted medical care consumption is within a 10 percentile range of the individuals' observed medical care consumption. For our model, this +/- 10 percentile match rate is 36.09 over the top quartile – and is 29% over the total distribution. When we examine the match rate of medical care expenditures when individuals predicted and observed health indices are within 10 percentiles of one another, the match rate for the top quartile improves to 41% and total match rate improves to 32%. For these statistics, our model does not represent a significant improvement when compared to the Grossman-consistent model. Where our model does outperform is the Grossman model is in predicting participation in the top tail of medical care consumers, as per our stated objective. Regardless of the model specification, the empirical implementation of joint conditional density estimation yields a meaningful improvement over traditional econometric methods. Whereas a conditional mean estimation captures 6% of the variation in health care expenditures, the joint CDE method yields a 32% match rate over a contiguous 25% interval when the health indices match – a 28% improvement over random outcomes.

C. Implications and Discussion

The finding that the change in health is relevant to the demand for medical care has theoretical, econometric, and policy implications. The theoretical model offers a clear explanation for high medical care spending. The equilibrium condition for health investment suggests that the change in health contributes to the marginal benefit from health and thereby increases the disequilibrium in the demand for health investment the more health changes, which justifies the observed large investments in medical care to regain equilibrium. Extant theoretical models either do not offer testable hypotheses on substantial medical care investments (Grossman, 1972) or rely on an unrealistic multiplicative functional form assumption for health depreciation to infer an increasing value of longevity (Ehrlich and Chuma, 1999).

The empirical finding that a 10% decline in health makes an individual 22% more likely to be in the top 5%, *after controlling for his or her state of health*, can help to explain why many in the top 5% of users nonetheless report relatively good health. In 2009 7.5% of the top 5% reported excellent health and nearly 20% reported very good health – more than the 18.5% who reported poor health (Schoenman, 2012). Our analysis suggests that these relatively healthy high users of medical care are distinguished from other relatively health non-users by the path of their health leading up to their high use. In other words, your demand for medical care is driven not by where you are, but how you got there.

The role of the change in health in the time path of medical care demand suggests that the change in health may be a driving factor in the increase in demand over time. As with the variation in health status, our finding on the change in health can explain why even though those over 65 are more likely to be in the top 5%, not all those over 65 are in the top 5%. Our analysis suggests that those seniors who experience a larger change in their health are more likely to be in the top 5%, and those who are already in poor health are more likely still.

The finding that the change in health is also significant to the demand for consumption has implications for modeling and interpreting the health-wealth gradient and the time paths of health and consumption. Estimates of the statistical value of a life year typically assume that health and consumption are complements and rise and decline together over the lifecycle. For example, Murphy and Topel (2006) assume the complementarity of health and consumption in their model and use this relationship to calibrate the time path of health based on the observed time path of consumption.[23] As a result, the rate of change in health is high between ages 50 and 70 and asymptotically declines at the end of life. This drives their conclusion that the value of a statistical life year peaks at age 50. However, neither is consistent with the observation that

[23] See Murphy and Topel (2006) p. 877 for the model and p. 887 for the time path of health.

individuals remain healthier longer, experience steeper declines in their health at much more advanced ages and appear willing to pay very high amounts on medical care at the end of life. More importantly, linking the time paths of health and consumption together a priori does not illuminate the mechanism that ties these two time paths together. This underlying mechanism may be essential to understanding the impacts of various policies, particularly in light of the finding that the demands for consumption and medical care are not separable.

Our time path of consumption combined with the empirical finding that health and consumption are complements or substitutes depending on the magnitude of the change in health suggest a mechanism whereby the time paths for health and consumption can diverge due to the interaction with the time path of medical care demand. Referring to the time path of consumption, equation (20)~~(20)~~, if the cross-partials between consumption and health and consumption and the change in health are positive as suggested by the empirical results, then the first term of the time path of consumption is consistent with Murphy and Topel (2006) in suggesting that as health declines consumption declines. However, the findings also suggest that the decline in health is associated with an increase in the demand for medical care. A positive $\dot{m}$ in the second term would mitigate the decline in consumption over time. In other words, there is both a direct (negative) and indirect (positive) relationship between the time paths of health and consumption. While we observe the two as complements, their rates of change are also impacted by the time path of medical care demand. If the time paths for health and consumption diverge such that health falls at a slower rate earlier in life and a faster rate later, then this would change the calculations of the value of a statistical life year in Murphy and Topel (2006) and imply a higher level of investment in life later in life consistent with observations of significant investment at older ages and among those in poorer health.

A focus on the change in 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% 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 finding 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 health care system and thereby end up in the top 5%. Third, incorporating the change in 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.

VI. Conclusion

We offer new theoretical and empirical insights into the predictors of high medical care expending. The distribution of medical care spending distribution is highly skewed, with the top 5% of spenders accounting for nearly 50% of expenditures. Nonetheless, most extant literature that estimates the distribution of medical care demand reports the fit at the mean or the median. Statistical models that fit the distribution do not offer policy-relevant insights into what drives high spending. While the top 5% is characterized by individuals who are older and sicker, not all old and sick people are in the top 5%, and significant proportion of the top 5% are younger and in relatively good health. Our theoretical model suggest that the change in health can help to explain high medical care spending and better predict who will be in the top 5%. To be able to estimate and simulate the full distribution of medical care spending we use a Conditional Density Estimator (CDE) with an eight-equation discrete factor random effects likelihood model that jointly estimates medical care spending, other consumption and the time path of health along with initial conditions for health and medical care spending. Our preliminary empirical results support the hypothesis that the change in health is a significant predictor of high medical care use. Using data from the HRS, the static marginal effect of a 10% decline in health is a 22% increase in the probability of being in the top 5% of the medical care spending distribution. Moreover, holding the 10% decline in health constant, but reducing the levels of both lagged and current health by 10% increases the probability of being in the top 5% by 180%. Thus, our preliminary estimates confirm the common-sense finding that poor health matters, but adds the new dynamic perspective that the path to poor health is also significant. When health states are close in the dynamic prediction of the model, we match the individuals in the top quartile of medical consumers at 42% and the top 5% at 18%. The predictive ability of our model exceeds the expectations of covariates that yield an R^2 of 6%. Nonetheless, ongoing research needs to identify covariates with better explanatory power for modeling the demand for medical care.

Appendix A: Notation

The following is notation for the theoretical model

U = Utility function; LU stands for lifetime utility.

H = State of health.

A = State variable for the change in health. $A \equiv \dot{H} = \alpha\left(t, m(t), H(t), \delta(t)\right)$

R = State of wealth

z = control variable for consumption of all commodities other than medical care including leisure time and non-medical care health related consumption such as diet and exercise.

m = Medical care including pharmaceuticals, procedures (e.g. heart surgery, X-rays) and physician visits but not including un-prescribed nutrition, exercise, supplements.

r = Constant real rate of interest.

δ = A deterministic function mapping time to the amount of health change as a function of time.

α = A deterministic function that maps time, units of medical care, the state of health and health depreciation to units of health change.

w = A deterministic function that maps the state of health and time to income including both wages and transfer payments (e.g. government disability, health insurance.)

P^m = Out-of-pocket point of purchase price per unit of medical care.

P^z = Price per unit of the composite commodity.

T = Terminal time (time of death.)

T_{max} = Maximum biological lifespan

H_{min} = Minimum health stock necessary to sustain life.

Appendix B: Health Index

Health Index Weights

Variable	Weight
Self-Assessed Health	
Excellent	1.241
Very Good	0.802
Good	0.145
Fair	-1.056
Poor	-2.81
Index of Activities of Daily Living	
0	0.392
1	-1.677
2	-2.497
3	-3.000
4	-3.401
5	-3.489
Index of Reported Health Problems	
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	0.18
2	-0.467
3	-0.947
4	-1.227
5	-1.539
6	-1.987
7	-2.501
8	-2.854

The Index of Activities of Daily Living includes bathing, eating, walking across a room, and getting in or out of bed.

The Index of Reported Health Problems includes: high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, psychiatric problems and arthritis. Respondents are asked if a medical professional has ever told them that they have one of these conditions. Prior responses are carried forward to subsequent waves.

The CESD Mental & Emotional Index is the sum of five negative indicators (depression, everything is an effort, sleep is restless, felt alone, felt sad, count not get going) minus two positive indicators (felt happy, enjoyed life) each with a 1-3 scale (never, all, most of the time). The resulting index has a a [0,8] range.

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Table 1: Variables Included in CDE Estimation

Initial Health	*2nd Period Health*	*Initial Medical Care*	*Initial Consumption*	*Per-period Consumption*	*Per-period Medical Care*	*Health Transitions*	*Probability of Death*
Age	Age	Age	Age	Age	Age	Age	Age
Age^2	Age^2	Age^2	Age^2	Age^2	Age^2	Age^2	Veteran
Education	Education	Education	Education	Education	Education	Education	z_t
Insured	Insured	Insured	Insured	Insured	Insured	Edu*m_t	Widowed
Married	Married	Married	Married	Married	Married		Unmarried
Kids	Kids	Kids	Kids	Kids	Kids		Kids
Region	Region	Region	Region	Region	Region	Region	
Veteran	Veteran	Veteran	Veteran	Female	Female	Female	
Parent's Alive	Parent's Alive	Parent's Alive	Parent's Alive	Black	Black	Black	
Mom's Age	Mom's Age	Mom's Age	Mom's Age	H_t	H_t	H_t	H_t
Dad's Age	Dad's Age	Dad's Age	Dad's Age	Wealth	Wealth	m_t	m_t
Physical Work	Physical Work	Physical Work	Physical Work	Income	Income	M_t^2	
Hazard Exposure	Hazard Exposure	Hazard Exposure	Hazard Exposure	ΔH	ΔH	z_t	ΔH
Strength Required	Strength Required	Strength Required	Strength Required	H_t *wealth	H_t *wealth	z_t^2	Mom's Age
				ΔH *wealth	ΔH *wealth	H_t * m_t	Dad's Age
				H_t *income	H_t *income	H_t * z_t	
				ΔH *income	ΔH *income		
				m_{t-1}	m_{t-1}		
				c_{t-1}	c_{t-1}		

Table 2: Summary Statistics

Variable	Mean	S. D.	Min	Max
Demographics				
Female	0.568	0.495	0	1
Black	0.146	0.353	0	1
Hispanic	0.089	0.285	0	1
Other Non-White	0.023	0.283	0	1
Health Index	0.764	0.172	0	1
Age	67.192	10.526	50	109
Married	0.436	0.495	0	1
No Sig. Other	0.094	0.291	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	1
Mother's Age (or Age at Death)	75.263	14.944	16	113
Father's Age (or Age at Death)	71.390	14.397	12	113
Death	0.024	0.155	0	1
Education/Human Capital				
Highest Grade Completed	12.052	3.393	0	17
High School Graduate	0.687	0.463	0	1
Attended College (1+ years)	0.384	0.486	0	1
College Graduate	0.180	0.385	0	1
Tenure at longest job (years)	20.728	11.842	0	1
Veteran	0.234	0.423	0	1
Strength Required (primary occupation)	0.654	0.925	0	7
Physical Demand (primary occupation)	1.37	8.49	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	2.224	0	15.02
Income (100K units, top coded)	0.491	0.538	0	5
Out of pocket med. exp. (100K units)	0.029	0.102	0	12.06
Calculated Consumption (100K units)	0.661	4.64	0	2.04
Individuals in Data Set	25,872			
Number of Observations	173,312			

Table 2a: Number of Observations Per Individual

Number of Individuals	Number of Observations (waves)
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 high numbers of individuals observed for 4 and 7~~7~~ waves are due to HRS adding respondents at waves 7 and 4 respectively.

Table 3: Parameter Estimates - Demand for Non-Medical Consumption

Variables	X		$X*\gamma_k$		$X*\gamma_k^2$	
	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
Mu 1	-0.042	***0.014				
Mu 2	-0.050	***0.010				
Phi 1	0.051	***0.014				

Table 4: Parameter Estimates - Demand for Medical Care

Variables	X		X*γ		X*γ²	
	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
Mu 1	0.873	***0.010				
Mu 2	-0.357	***0.012				
Phi 1	2.362	***0.038				

Table 5: Parameter Estimates - Health Transition

Variables	X		X*γ		X*γ^2	
	Estimate	**Std. Err**	**Estimate**	**Std. Err**	**Estimate**	**Std. Err**
Constant	6.845	***0.629	2.779	***0.699	1.688	***0.197
Lagged Health	-10.577	***0.226	-2.652	***0.162	-0.551	***0.036
Age	7.306	***1.789	3.137	2.031	0.090	0.560
Age Squared	-0.162	0.134	-0.120	0.151	0.194	0.410
Lagged Medical	-18.563	**7.142	-5.263	5.743	0.139	1.167
Lagged Health*Lagged Medical	20.339	**8.096	6.365	6.468	-0.003	1.134
Years of Schooling	0.050	***0.006	0.098	***0.006	0.018	***0.002
Years of School*Lagged Medical	0.013	-0.116	-0.035	0.044	0.268	0.239
Lagged Consumption	-0.024	0.217	-0.029	0.048	0.001	0.013
Northeast Region	0.055	*0.030	0.058	***0.013		
Western Region	-0.143	***0.028	-0.015	0.013		
Midwest Region	0.194	***0.025	0.123	***0.012		
Black	0.297	***0.069	0.072	0.072		
Female	0.087	***0.031	0.183	***0.037		
Lagged Health*Lagged Cons.	-0.288	0.255	0.015	0.232	0.018	0.052
Mu 1	-1.216	***0.011				
Mu 2	1.096	***0.011				
Phi 1	-0.014	0.015				

Table 6: Parameter Estimates: Initial Conditions - Health

Variables	X		X*Y		$X*Y^2$	
	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
Mother's Age	1.039	*0.542	0.952	*0.511	0.159	0.121
Father's 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	-0.597	0.409	-0.222	0.180		
Mu 1	2.896	***0.029				
Mu 2	1.238	***0.022				

Table 7: Parameter Estimates - Initial Conditions - Medical Care

Variables	X		X*γ		X*γ^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
Mother's Age	0.198	0.520	0.373	0.559	0.108	0.144
Father's 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	-0.362	0.037				
Mu 2	-0.076	0.036				

Table 8: Marginal Effects on Outcomes of Interest – (in response to 10% positive change for continuous variables)

Variables	Medical Care			Consumption			Health		
	Bottom Quartile	Inter Quartile	Top Quartile	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%	4.4%	7.7%	9.1%
Change In Health	-10.5%	-14.1%	-18.5%	-3.8%	-4.0%	-1.4%	-4.2%	-1.4%	-0.8%
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%	-4.1%	-2.3%	-1.4%
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%	-2.4%	-1.8%	-0.7%
Female	14.2%	-10.1%	-18.0%	1.7%	2.2%	2.7%	12.2%	6.5%	2.2%
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%	0.8%	0.6%	0.4%
Lagged Consumption	-2.5%	-0.8%	1.1%	1.0%	-1.0%	-1.0%	-0.3%	-0.5%	-0.7%
Lagged Health*Lagged Medical Care							-0.5%	-4.4%	-2.5%
Years of Schooling * L. Medical Care							0.1%	0.0%	-0.1%
Lagged Health * Lagged Consumption							0.0%	0.0%	0.0%

Figure 1: Kernel Density Plot of Observed and Predicted Health Indices

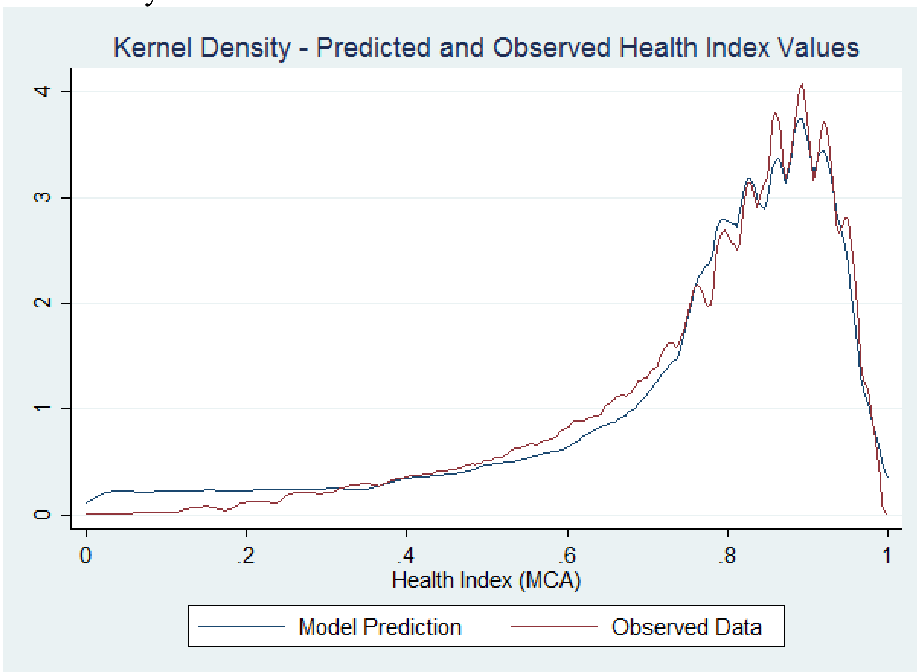

Figure 2: Kernel Density Plot of Predicted and Observed Consumption

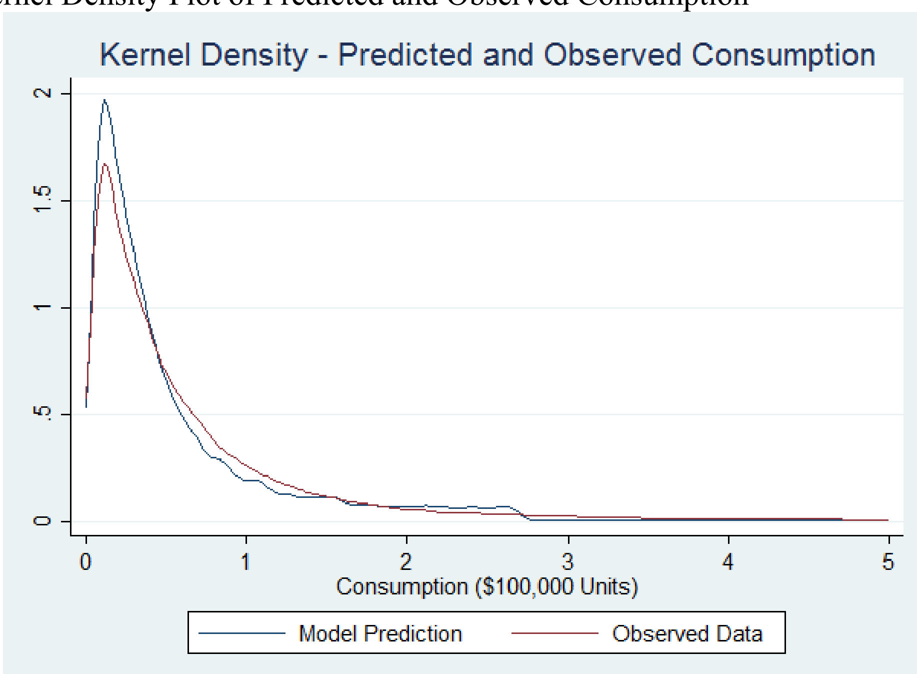

Figure 3: Kernel Density Plot of Predicted and Observed Medical Expenditures

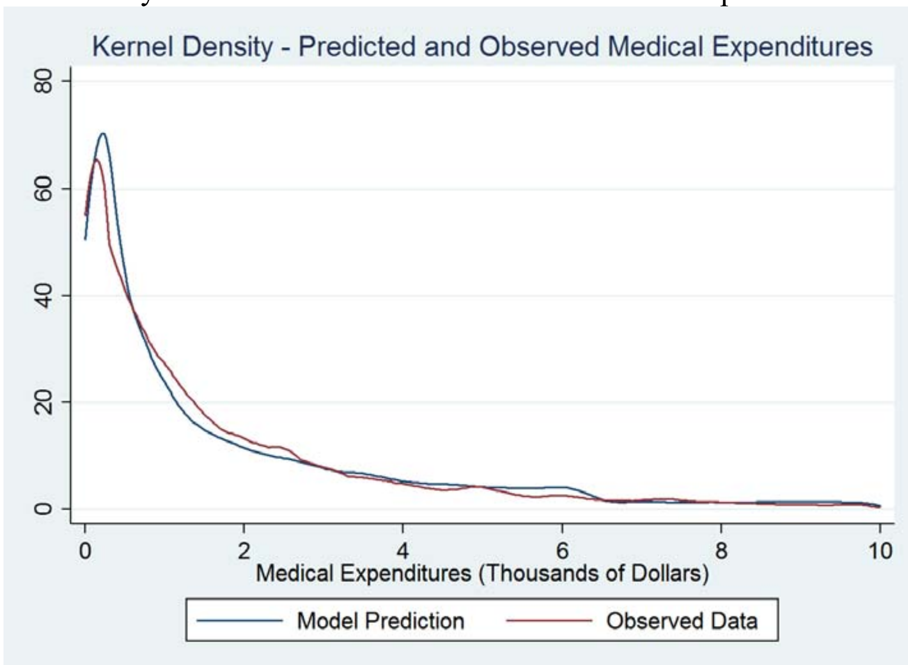

Table 9: Summary Statistics of Top 5% of Medical Care Consumers - Model Prediction vs. Observed Data

Variable	Observed Data	Our Model	Grossman-Consistent Model
Age	70.70	**70.77**	73.392
Health Index	0.636	**0.594**	0.353
Change In 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	0.560	0.432
Lagged Med. Care	0.037	**0.033**	0.055

Text in bold indicates one model is closer to the observed data with 5% significance.