The Dynamics of Health Care Demand During an Illness Episode

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Abstract

Previous studies assume consumers make medical care choices over large (e.g. yearly) time steps. However, most health expenses occur in the weeks immediately following a shock to health. It is unknown whether demand during an illness episode differs from "normal" long-run demand. How do consumers make the sequential, dynamic choices to consume medical care during an episode of severe illness? A theory of the consumer's short-run health investment is offered and tested empirically using the Medical Expenditure Panel Survey. It is found that demand is extremely price inelastic immediately following the shock, but is very responsive to changes in health.

I. Introduction

Health economics has been studied with increasing fervor in recent years, and this is not without due reason. In the US alone the cost of care has grown at an alarming rate, well outpacing growth in per capita GDP and projected to encompass as much as twenty-five percent of total GDP in the coming decades (Orszag, 2008). Previous research confirms that rising prices encourage over-insurance (Feldstein 1973) and expose individuals and families to greater expenditure risk as larger portions of their wealth are tied to uncertain health. Demand for insurance increases as families seek to defray this risk, and the rising premiums that result block millions of other consumers from accessing affordable care across the US. As a result, differences in health insurance coverage, and thus health outcomes, have been linked to various calamities—the perpetuation of racial inequality (Weinick, Zuvekas, and Cohen, 2000), income inequality (Schoen et al., 2000), and variations in health capital with important implications for economic growth (Hartwig, 2009 is a good review of this literature), to name only a few. Understanding how, and when, individuals make choices to consume medical care is foundational to understanding their exposure to expenditure risk and the incentives that drive the upward spiral of costs.

In applied studies, if a theoretical framework is offered it is based, at least in a loose sense, on the Grossman (1972) concept of health capital investment. In Grossman's conception, health capital is an essential component of human capital. It is produced for its own utility and for the sake of consuming other goods. As a result, health itself and not health care enters the individual's utility function. Individuals adjust medical care in discrete time steps[1] and set optimal levels of health based on deterministic health stock, lifetime utility, and permanent income considerations. Hence, demand for medical care is a derived demand, intended as an input to maintain a desired level of health.

Most previous studies assume that the time steps over which individuals make health care decisions is large, such as on a year-to-year basis. At the beginning of each year, the consumer assesses his health and the amount of care needed to maintain his stock of health. He obtains the amount of care that equates marginal benefit to marginal cost, producing lifetime steady state levels of health and investment through medical care. The framework often does well to explain health producing behaviors over large time spans, for example physician checkups or optimal diet and exercise (Huston and Finke 2003).

There are basic shortcomings to the assumption of large time steps, however. Chief among these shortcomings lies in ignoring the uncertainty of health capital. Empirically,

[1] In this context, a time step is simply a length of time over which a person's choices are fixed.

the processes which govern deterioration of health and the effectiveness of health care are never deterministic. Under uncertainty over health, consumers will theoretically hold higher long-run equilibrium levels of health capital (Cropper 1977; Muurinen 1982; Dardanoni and Wagstaff 1987, 1990). For example the incident of heart attacks, infections, and cancer are at least partially random, as are the prices and marginal product of medical care to treat these illnesses. After a shock, the exact marginal benefit of care is unknown because whether a particular drug or therapy will work for the given patient is random[2]. Hence, the set of treatments must be reassessed periodically to ensure the consumer's health improves over time, and to ensure that the consumer's demand is utility maximizing.

Following a severe shock, it is doubtful that these adjustments occur on the same large time step basis, e.g. year-to-year, that describes the consumer's long-run demand for care. Both empirically and practically, these reassessments of the patient's stock, treatment bundle, and prices must take place over smaller time steps such as on a daily, weekly, or even monthly basis. Consider a hypothetical individual who has just experienced a heart attack. The physician immediately performs surgery and prescribes medication to save the patient's life. Does the physician then wait one year to see if the patient survived? Does the patient allow this to happen? Clearly not.

The effectiveness of the surgery and medication is uncertain, so the consumer is enticed to ensure he is actually healing from the attack. The physician and patient meet the next week and reassess the patient's health and cost of care, and then adjust treatment accordingly. For example, if the medication is ineffective or too expensive, a substitute medication might be prescribed. The week-to-week reassessments continue and medical care demanded is likewise adjusted until the consumer is eventually satisfied with his long-run level of health[3].

It is erroneous to assume that an aggregated year-to-year decision captures all of the dynamics of the choices to assess and update demand during an illness episode. Since uncertainty implies that shocks to health induce such episodes, there must be a "short-run" period of adjustment over which the consumer temporarily makes choices in smaller time steps[4]. Estimation of this short-run adjustment problem is largely ignored by the literature, even though it is foundational to understanding how and when consumers demand most medical care. This study asks the question: How do consumers make sequential,

[2]This very realistic, as treatments and drugs are usually characterized by the distribution of their effectiveness within the population. The physician does not know where the patient falls within that distribution.

[3]This can either be his old level of health or a new one, depending on the severity of the shock

[4]That is, the period over which choices are fixed is temporarily shorter.

dynamic choices to consume medical care during an episode of acute or chronic illness? Is the information captured by these short-run choices different from that uncovered by previous long-run demand estimates?

This paper immediately distinguishes itself from previous literature by directly analyzing dynamic demand during an illness episode, when patients and physicians adjust and update treatment due to random treatment effectiveness and prices. A better understanding of the incentives that govern the adjustment back to long-run steady state demand and health are important to addressing other overarching issues in health economics. Gilleskie (1998, 2009) are the only remotely similar treatments known to this author, and no previous study has addressed demand after a *severe* shock. Moreover, this paper is a novel treatment of demand choices that comprise the majority of health care expenses, as more than half of all medical expenses are incurred during these chronic episodes (Machlin, Cohen, and Beauregard, 2008) or when treating acute illnesses.

This paper is secondly unique in its theoretical offering. The conceptual literature ignores heterogeneity of time steps after a health shock and the short-run, small time step adjustment path that follows. As will be seen, the importance of this path is well motivated empirically. The portfolio framework this paper offers and the stochastic decision tree that directly follows tie the short-run problem into the well understood lifetime health capital theory of medical care demand.

This study is finally novel in its empirical offering. The model's intuition motivates a straightforward empirical exercise which has never before appeared in the literature: an estimate of dynamic short-term demand for medical care following a severe health shock. The empirical exercise tests whether demand during the adjustment period is indeed different from demand over large time steps. The richness of the Medical Expenditure Panel Survey (MEPS) is exploited to do so. The results shed new light both on the acceleration of cost as well as on efficiency of equilibrium in "over-insured" markets.

For organizational purposes, the paper proceeds as follows. Section II offers an overview of the literature pertinent to the study. III outlines the theoretical model in detail, both short and long-run, and motivates the empirical exercise that is the paper's focus. Section IV describes the empirical strategy and data, while V presents the results and discussion. VI offers concluding remarks.

II. Literature Review

A study of demand for medical care after a health shock is interesting for numerous reasons, and though the literature directly analyzing demand during acute and chronic illness episodes is sparse, its potential implications are vast. A discussion of the broader implications for previous empirical research is left for the results section, as it is tangential to the theoretical and empirical arguments which are this section's focus. In the theoretical literature on health capital, special attention is paid to the role of uncertainty in the model, since uncertainty over health stock and over the effectiveness of health care induce the short-run adjustment problem in the first place[5].

Grossman (1972) introduced the notion of health capital. Grossman observed that, unlike in a market for traditional goods, people did not value medical care for its own sake. Rather, they value the health that the medical care produced, for its ability to maintain their stock of human capital for other consumption[6]. In Grossman's health investment model, health and not health care enters the utility function and individuals receive utility from health and other consumption. He assumes the production function for income is an increasing function of health stock: the healthier the individual the higher his wage, the more time to work, etc. The agent produces, or more aptly maintains, health capital because it both makes him happy and affords income by which his consumption of other goods ultimately increases. In the health investment model the consumer maximizes lifetime utility subject to permanent income, investment in and deterioration of health capital stock, and restrictions on usage of time. The solution to the problem results in a optimum level of health capital stock and an optimal level of investment for each discrete point in time.

Grossman's conception is novel but not without flaws. First is the assumption of uniform time steps for decision making throughout the consumer's lifetime. The mathematics of the model do not depend on the size of the time step, implying that the utility maximizing behavior only depends on the choices being made. Yet, for analytical purposes it is assumed that the time step is fixed throughout the consumer's life. Making this uniform time step assumption has serious implications for applied work, as the investment model provides excellent intuition but is not a tractable, closed-form theory for empiricist to easily employ.

One implication is that most empiricists assume decisions are made on a year-to-year basis. Medical care only arises as an investment in health to stave off or repair deterioration to health stock[7]. Given this, the consumer must be capable of perceiving

[5]It should be noted throughout the exposition that almost every application of the theory assumes the relevant decision time steps are large, such as year-to-year, and uniform. Hence, they only address long-run steady state responses to the *risk of a shock*, and not peoples' actual responses *to the shock* during an illness episode. The response is assumed instantaneous.

[6]Grossman outlines two models in his original paper, one for consumption and one for investment.

[7]Health care demand is a derived demand somewhat analogous to demand for factor inputs in classical producer theory. Intuitively, then, it is expected to be compensated in the long-run optimal level of health capital, less elastic than typical Marshalian demand, and possibly zero at any given point in time, via compensated in health stock. Grossman's "threshold" emphasizes this point, there is a threshold of health beyond which the consumer demands no medical care. An excellent example of data phenomenon

his health stock over the entire year, otherwise he cannot choose the investment that equates marginal benefit to marginal cost. Clearly this assumption is only reasonable in limiting contexts, where the occurrence and effects of disease as well as the marginal product of care are known by the consumer with certainty. For example, year-to-year care for high cholesterol or perhaps adjustments in diet to treat diabetes are well described by such a model.

However, most medical expenses do not meet these criteria (Machlin, Cohen, and Beauregard, 2008). Instead, most are incurred adjusting care for the random effectiveness of treatment and for the uncertain evolution of health stock in the weeks and months immediately following a shock to health. For the introduction's example of a hypothetical heart attack patient, treatment was reassessed on a weekly basis to account for this randomness. Previous studies have not allowed for different time steps in the consumer's lifetime problem, one for illness episodes and one for long-run decisions. Additionally, no previous study has contrasted demand for medical care in each context.

A second shortcoming of Grossman's uniform time step assumption is it predicts that health and medical care consumption will be positively correlated, since greater investment equates to higher health in the long-run. Empirically, though, health and medical care are negatively correlated[8]. This is intuitive, since one expects an individual to consume more care when sick than when well. The literature exploring this negative correlation is vast but includes two convincing explanations. The first is that health capital does not adjust instantly in response to medicare care (Wagstaff, 1986). The mere existence of such a path in long-run estimates fits consumption data well (Wagstaff, 1993), even though the adjustment path itself is never estimated in the literature.

A second explanation is that consumers choosing not to purchase medical care are at a corner solution of their health investment problem. Allowing for a corner solution, examining a cross-section of medical care consumers will lead to a negative correlation between health and medical care since healthy individuals will consume no care (Galama and Kapteyn, 2009). Of course, neither explanation is mutually exclusive and, when coupled with the existence of a negative health shock, begs an empirical study of the short-run adjustment problem. That no such study has appeared in the literature constitutes a clear gap in economists' understanding of how consumers demand medical care.

The next weakness of Grossman's conception lies in the incorporation of uncertainty in the model. Potential sources of uncertainty are easy to imagine, for instance the exact

is zero-inflated expenditures. Many individuals will consume no health care within a period, and those that do consume behave as if it is a necessity.

[8]For example, see Wagstaff (1986).

incident of cancer is unknown, as is the chance a particular antibiotic will effectively treat a bacterial infection. Reconsider the case of the hypothetical consumer after a heart attack from the introduction. If the heart attack were foreseeable, as in Grossman's model, then the consumer would have acquired the care to prevent the attack and his health would adjust to equilibrium levels instantly. Depicting consumption this way is unreasonable due to randomness in health shock and in the effectiveness of health care. More realistically, the consumer may be very concerned about the effectiveness of care along the short-term adjustment path, since his health capital impacts his grander human capital investment choices (Muurinen, 1982).

Numerous studies have incorporated randomness into Grossman's investment framework[9]. Typical of the findings is Dardanoni and Wagstaff (1987), who aim to ascertain the interaction of uncertainty over health and income inequality. They show that, assuming random health, initial wealth endowments matter a great deal in determining long-run optimal levels of health capital. This is contrary to Grossman's original result, where health investment at any given stage in life is independent of initial wealth. Dardanoni and Wagstaff (1990) explore this issue further by allowing medical care to be randomly effective. Individual's maximize lifetime utility in each period by equating the discounted marginal benefit of increased health to the marginal cost of the health investment. Surprisingly, uncertainty over health and the effectiveness of medical care only changes this basic story slightly. Covariance terms arise in the First Order Conditions of optimality that, under reasonable assumptions such as risk aversion, would lead the consumer to purchase more medical care than he otherwise would under certain health. Picone et. al. (1998) affirm this result and explore the implications of varying degrees of risk aversion. On a year-to-year basis, for instance, they show that the consumer's risk preferences matter a great deal to the "smoothing" of health investment over the individual's lifetime.

The basic intuition of all the lifetime models in each case only affirm Dardanoni and Wagstaff (1990)'s foundational results[10]. The evolution of health capital over time follows

[9]Early in the literature, Cropper (1977) allows mortality rates to be random. Over large time spans, individuals precociously invest in health to decrease the odds death and disease, but the care itself is not randomly effective. Cropper shows that Grossman-style deterministic health stock underestimates the demand people place on preventative health care when any degree of uncertainty exists over their health. Hence, if the consumer is risk averse then there is a clear incentive to insure against the expenditure risk imposed by negative shocks to health.

[10]Though they are all not addressed fully here, notable extensions are as follows. Liljas (1998) produces a model in which the deprecation of health explains the degree to which the consumer will insure themselves against potential shock. The deprecation of health stock is dependent on the level of health; optimal insurance levels arise in long-run steady state to maintain utility maximizing health stock. The optimality of Liljas (1998)'s insurance is doubtful but one incentive is clear: individual's are more likely

a deterministic component (e.g. aging, diet and exercise) as well as a random component (e.g. accidents, cancer, heart attacks). The health capital framework is sensitive to the type of uncertainty and not just uncertainty itself. If randomness is allowed to separately impact both the occurrence of illness and the effectiveness of medical care, then long-run average levels of health stock are higher, and the poor might be less attracted than the wealthy to the health investment due to the uncertainty. No previous study has incorporated randomness into the short-run adjustment path after a health shock.

Given uncertainty over health stock, individuals from time to time will find themselves below their optimal level of health and must thus consume health care until back to normal levels. Since most are informed of illness by a physician, people rarely know their exact health stock and amount of needed care until already sick. Over half of all medical expenditures are incurred during acute or chronic illness episodes. Yet, the focus of the aforementioned literature remains on the long-run conception of health capital—a problem better suited for understanding lifetime levels of health and insurance but not necessarily suited for understanding demand for physician visits or prescription drugs in response to a negative shock to health.

Gilleskie (1998) is the first direct treatment of the short-run problem. Gilleskie focuses on worker absenteeism, but also models health care demand during acute illness episodes 21 days or less for less severe inflictions (e.g. flu, cold, accident, etc.). In Gilleskie's model, individuals trade between time off work and the consumption of medical care in order to return to normal health . Structural equations, rather than reduced-form estimation, are used in the empirical exercise. Gilleskie (2009) extends the work, attempting to understand the differences between men and women as they respond to acute illnesses. Gilleskie's framework is important in that it affirms that consumers adjust demand over smaller time frames after a health shock.

Gilleskie's work has many shortcomings, however. First, illness episodes driven by the flu, colds, or minor accidents do not usually pose large expenses nor are they fearful for the consumer. This is important since it is still unknown in the literature how consumers adjust to a *severe* health shock over longer periods of time. Second, uncertainty is not

to fully insure if health shocks impose risk to long-run optimal consumption and health. Jacobson (2000) supposes that health capital decisions are made at the family, rather than individual, level. This interweaves the utility functions of each family member. Unsurprisingly, if a family member's health is at risk then one's own utility falls, meaning the basic uncertainty results already established are amplified in the family-level utility model. More recently, Laporte and Ferguson (2007) make health fully stochastic in continuous time. They consider the implications of a Poission shock to health. This allows the consumer to adjust "instantaneously" to health shock by consuming care, and hence ignores the fact that consumer treat illness with a sequence of, for instance, physician visits. However, since the utility maximizing behavior is invariant to the time step, the results do not differ substantially from previous knowledge.

incorporated in the dynamic programming model. This is likely because uncertainty in treating the illnesses Gilleskie examines may be small and fairly inconsequential for individuals both financially and in terms of short-run health. Empirically, the effectiveness of care varies widely over the adjustment period. As is shown in the next section, unlike in the long-run open-ended random extensions of Grossman's model, feasible short-run random paths are likely mean-reverting or closed-ended stochastic bridges. This calls into questions the consistency of any empirical estimation which does not explicitly take such a path into account, including Gilleskie's work.

Finally, Gilleskie models daily decisions but does not consider whether time steps are different between illnesses or whether demand over the episode differs from demand estimated in large time steps, such as on a year-to-year basis. Uncertainty clearly plays a role in determining the long-run steady state of health, so it is natural to question how consumption after a severe shock converges to the long-run steady state. Such a comparison is lacking in the literature but potentially has profound explanatory power. Does an individual at a corner solution of health investment respond to shock differently compared to an individual already in poor health? If the shock is particularly severe, is it possible that long-run optimal health can never again be achieved? If so, how do consumer's invest in health to re-devise their long-run steady state? These questions are unanswered by the literature but have powerful implications for a consumer's welfare.

Within this context, this paper contributes to the literature in two ways. First, it distinguishes itself from previous literature by directly analyzing dynamic demand during a severe illness episode. It generalizes the theoretical literature on health capital into a portfolio allocation problem over health inputs. It is the first to question the uniformity of decision time steps in a Grossman model in order to explain various data phenomenon, such as health investment corner solutions and the negative correlation between health and medical care. Secondly, the paper is the first to compare demand during an illness episode to its long-run counterpart. This comparison tests whether price responsiveness and potentially risk aversion in the short-run differs from the long-run steady state. The welfare, insurance, and policy implications of the dynamics are addressed. The following section outlines this model in detail, while sections IV and V outline the empirical heart of the study.

III. Theoretical Framework

Recall that the overarching research question of the thesis is: How do consumers make sequential, dynamic choices to consume medical care during an episode of acute or chronic illness. This section's goal is to illustrate the utility maximizing behavior of the consumer over his lifetime. For the sake of presentation clarity, the following model assumes that health only affects the individual through his production of income and also ignores randomness[11]. The case where the individual derives utility from health stock as well is considered outside of the main text, the interested reader may consult Appendix A. However, the overarching interpretation of the model is similar in all cases.

The Lifetime Utility Problem

The lifetime problem sets the long-run utility maximizing level of health capital stock for the individual. Individuals are utility maximizing, forward looking in their choices, and have some function $\psi(H_t, \cdot)$, increasing in health stock, that defines the benefit received from increased health. One need only consider a value function of two periods of consumption to uncover the First Order Condition of particular interest.

	Model Summary
$H_t(\cdot)$:	Health capital stock in period t, an increasing function of health investment.
δ:	Depreciation rate of health capital per period.
$\psi(H_t, \cdot)$:	Income as a function of health (due to healthy time, etc.), an increasing function of health stock.
M_t:	Medical care health inputs in period t.
$I(M_t)$:	Health investment function, maps a portfolio of medical care inputs to health stock.
C_t:	Consumption in period t.
$\sum \beta^t U(C_t)$:	Additively separable lifetime utility w/ discount rate β
P_m:	Price of medical care inputs.

The consumer's lifetime utility maximization problem is exemplified by two periods of utility $U(C_t) + \beta U(C_{t+1})$, where utility is assumed continuous, increasing, and concave in consumption ($U' > 0$ and $U'' < 0$). The t period budget constraint as a savings relation is $S = \psi(H_t) - C_t - P_M M_t$. With a per-period interest rate r the resulting second period budget constraint is $C_{t+1} = (1+r)S + \psi(H_{t+1}) - P_m M_{t+1}$. For clarity, an example of the income function is the process $\psi \sim y_t + \psi(H_t)$ where y_t is a "basic" level of income and $\psi(\cdot)$ is additional income tied to health stock, such as healthy time to work. Assume ψ is continuous and increasing in health stock, $\psi' > 0$.

[11]This admittedly appears hypocritical given the discussion of the literature review. However, the foundational utility maximizing behavior of the consumer does not change when randomness is introduced. Randomness does induce the short-run adjustment problem, though.

The consumer is granted an initial health stock H_t and a depreciation rate δ reduces stock between periods. $I(M_t)$ is a health stock investment function choosing a portfolio of health inputs (medical care, diet, etc.). Assume $I(\cdot)$ is continuous, increasing, and concave in medical care inputs as well, $I' > 0$ and $I'' < 0$. Concavity of $I(\cdot)$ over the health portfolio reflects the complementary nature of health inputs, for example prescription drugs and physical therapy working together to achieve higher health levels[12]. By net investment, health stock in period $t+1$ is $H_{t+1} = (1-\delta)H_t + I_t(M_t)$. With this, the consumer's lifetime utility maximization problem is:

$$\max_{C_t, M_t} U[C_t] + \beta U[(1+r)(\psi(H_t) - C_t - P_M M_t) + \psi((1-\delta)H_t + I(M_t)) - P_m M_{t+1}]. \quad (1)$$

Noting that the maximization is with respect to the previous period budget constraint[13], the first order conditions are:

$$\text{FOC on } C_t : U' + \beta(1+r)(-1)U' = 0 \implies \beta = \frac{1}{1+r}. \quad (2)$$

$$\text{FOC on } M_t\text{: } \beta(1+r)(-P_m)U' + \beta U'\psi' I' = 0 \implies P_m = \beta\psi' I'. \quad (3)$$

Which together imply that in each each period:

$$\frac{P_m}{I'(M_t)} = \frac{\psi'(H_t)}{1+r}. \quad (4)$$

(4) states that individuals invest in health until the discounted benefit to their welfare is equal to the marginal cost of the investment. The same basic behavior is also uncovered when the consumer receives utility from health, as well as when uncertainty is allowed to affect health stock and the marginal product of medical care[14]. For larger time steps t, such as year-to-year decisions, it is useful to denote the consumer's long-run optimal steady state health stock by H^*.

The Illness Episode Problem

Now assume that uncertainty over health stock exists and that a severe random shock to health occurs, knocking the the consumer out of long-run steady state[15] and leading the

[12]It is also possible that inputs are substitutes and not compliments. In this case, the second derivative condition need only reflect decreasing returns to a single input.

[13]Hence M_{t+1} is not in the maximization argument. This ignores the trade-off between medical care now and medical care consumed later. In Appendix A this trade-off is explored.

[14]See Picone et. al. (1998) and Galama and Kapteyn (2009)

[15]Recall that the notion of long-run steady state implies large time steps, such as year-to-year decisions.

consumer to purchase medical care. Suppose that the time step over which adjustment occurs after a shock is shorter than the one which well describes the consumer's lifetime steady state. That is, the period over which this medical care is adjusted after a shock is short but not insignificant, such as on a week-to-week or month-to-month basis. Since the individual is lifetime utility maximizing, and since the mathematics of the lifetime problem are independent of the size of the time step, he must either once again settle to a long-run steady state exemplified by his year-to-year decisions, or re-devise a new steady state based on his obtainable health stock[16].

This utility maximizing behavior places boundary conditions on the adjustment path. If one allows shocks and random effectiveness of medical care within the episode, then the adjustment of health over the episode is a stochastic path. Though this stochastic path is discussed further below, the probabilistic nature of the path guarantees that a probability measure exists which captures the information of each choice to consume or not consume throughout the episode.

Denote the length of this short-run time period as $0 \leq t \leq T$, and discretize it such that each step $\triangle t$ is taken over n steps with $n\triangle t = t$[17]. For some N number of total steps in the episode, $N\triangle t = T$. The consumer has a short-term welfare function $\tilde{\psi}_t(H_t)$ that is increasing in health stock as before and has the terminal condition $\tilde{\psi}_T(H^*) = \psi_T(H^*)$ to nest the problem within the long-run steady state: when the consumer has adjusted to steady state demand. The short-run investment function is $\tilde{I}_t(M_t)$, and the consumer's problem is to assess and adjust a portfolio of medical care inputs at each time step such that normal health levels are ultimately achieved through $\tilde{I}_t(\cdot)$. At each stage the consumer picks the amount of medical care that equates marginal benefit to marginal cost. This is just as before, only now choices are made in temporarily smaller increments.

Over the illness episode it is difficult empirically to differentiate between "quantities" of medical care, for example distinguishing outpatient from normal office-based care. For sufficiently small time steps, that utility maximizing behavior may also lead to zero consumption in the health investment portfolio. For empirical convenience it is useful, then, to adopt a probabilistic interpretation of demand over the illness episode. Fix M_t as a binary choice to consume or not consume medical care at period t, note that because M_t is binary the $Prob[M_t = 1]$ is the probability measure which captures all information reflected in the consumer's health portfolio adjustment choices[18].

[16]The later situation is the case of a chronic illness, when original health is never again achievable. This is acceptable for the problem at hand, as the only concern is that some sort of long-run steady state is once again achieved.

[17]Take note that here $\triangle t$ is much smaller than the t considered in the utility maximization problem.

[18]At first glance this assumption limits the analysis. However, it is necessary in order to consider the

Under this assumption the model of demand during the episode is really just the formalization of a decision tree branching at each $\triangle t$ node. The episode starts at low, shocked health stock H_0, at $n\triangle t = 0$. The empirically observed choice rule for an arbitrary period t is:

$$M_t = \begin{cases} 1 & , \text{ if } \frac{\tilde{\psi}_t\left((1-\delta)H_{t-1}+\tilde{I}_t(M_t)\right)}{(\tilde{I}_t(M_t)-\delta H_{t-1})(1+r)} \geq \frac{P_m M_t}{\tilde{I}_t(M_{t-1}+M_t)} \\ 0 & , \text{ if } \frac{\tilde{\psi}_t\left((1-\delta)H_{t-1}+\tilde{I}_t(M_t)\right)}{(\tilde{I}_t(M_t)-\delta H_{t-1})(1+r)} < \frac{P_m M_t}{\tilde{I}_t(M_{t-1}+M_t)} \end{cases}. \tag{5}$$

The rule in (5) is simple: the individual compares the discounted benefit of consuming medical care to the additional cost of acquiring the care. If the benefit of an input is at least as great as its cost, then in period t we observe medical care consumption. If the cost outweighs the benefit, then the individual does not consume[19].

The choice is the same at each node n so that in time period t the individual decides to consume medical care in period $t+\triangle t$ only if the marginal benefit equals the marginal cost. Observe that for small changes in medical care consumption and small time steps we have $\frac{\tilde{I}_t(M_t+M_{t+\triangle t})}{M_{t+\triangle t}} \approx \tilde{I}_t'(\cdot)$ and $\frac{\tilde{\psi}_t\left((1-\delta)H_t+\tilde{I}_{t+\triangle t}(M_{t+\triangle t})\right)}{(\tilde{I_{t+\triangle t}}(M_{t+\triangle t})-\delta H_t)} \approx \tilde{\psi}_t'$, and (5) reduces to the FOC of the lifetime health investment problem. Hence, the model is consistent with the same type of utility maximizing behavior the consumer displays in the lifetime problem, only now with potentially different income and investment functions.

The above choice rule only differs from the lifetime steady state choice by an additional constraint: that by some finite period N, at $N\triangle t = T$ time, enough health investment must occur to achieve a long-run steady state H^*. This implies that certain paths in the tree are not feasible, namely those with too few choices to consume, since they prohibit H^* from being achieved. Graphically, Figure 1 depicts the $\{0,1\}$ decision to consume across the period.

There is a probability p_t at each step that the individual will consume care, where p_t captures all of the information of the decision rule to equate marginal benefit with marginal cost at each node. Observe that health improves with each "up-tick" and deteriorates otherwise. Also note that, if there is a random component in the adjustment of health, then there is some small chance that the consumer can achieve H^* without medical care.

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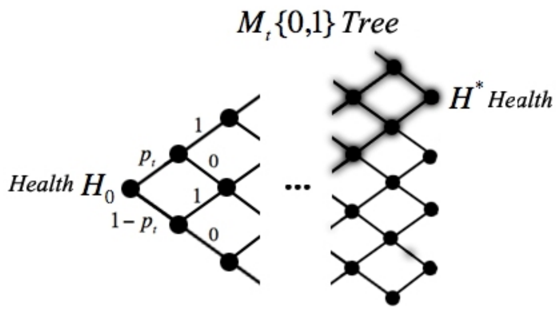
consumer's holistic portfolio problem over numerous medical care inputs.

[19]In reality, M_t is a vector of inputs and choice rule above applies to each vector component. Each input is adjusted until the overall net benefit of the portfolio equates to its marginal cost.

Figure 1



The prohibited branches not resulting in H^* are worth exploring, since there is a differential path health stock must follow across the period. We want to allow the evolution of health to be random, so define B_t to be a random shock between periods. Intuitively this captures the random effectiveness of medical care and the potential for additional shocks to health. Then, if no branches were prohibited, the probability mapping describing the decision tree's impact on health stock would be a simple binomial tree. In this case, by net investment health stock would evolve across periods according to $H_{t+\triangle t} = (\tilde{I}_t(\cdot) - \delta)H_t \triangle t + \sigma H_t B_{t+\triangle t}$, where σ is the standard deviation of the health stock due to the shock.

However, since the terminal condition H^* is enforced at $N\triangle t = T$, the evolution of health over the period is not open ended. At each node, the consumer is clearly concerned with ultimately achieving normal health. Hence, a relevant measure of the marginal impact of the consumption choice is the period-discounted distance between current health and ideal health, or $\frac{H^* - H_t}{N\triangle t - n\triangle t}$. Putting it all together, health stock must evolve between choice nodes according to a modified net investment formula:

$$H_{t+\triangle t} = [\tilde{I}_t(\cdot) - \delta]\frac{H^* - H_t}{(N-n)\triangle t}\triangle t + \sigma H_t B_{t+\triangle t}. \tag{6}$$

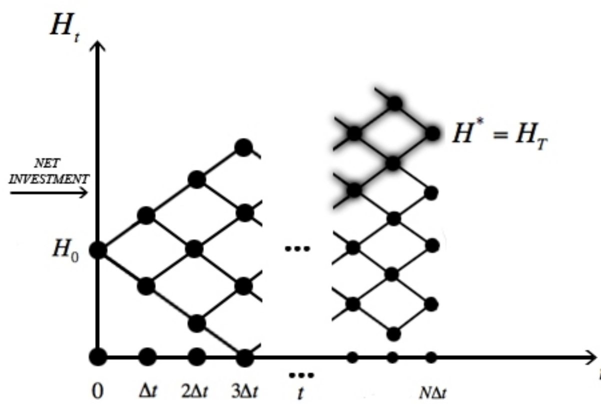
(6) states that the consumer may increase health by a factor of $\tilde{I}_t(\cdot) - \delta$ at each choice. From the convergence fraction, the consumer is concerned with achieving normal health at each node in the episode as $n \longrightarrow N$. If the consumer is lucky, $\sigma H_t B_{t+\triangle t}$ will fall in his favor and the constraint will be less binding. If he is unlucky, $\sigma H_t B_{t+\triangle t}$ forces more medical care consumption that he would otherwise have preferred. The evolution of health described above is known as a stochastic bridge[20]. The stochastic bridge grants the existence of the probability measure p_t. Hence, the consumer's problem at each choice

[20] An illustration of such a bridge driven by brownian motion is provided at the end of Appendix A.

node in the tree is to assess the discounted net benefit of additional medical care subject to the constraint that health evolves according to this stochastic path.

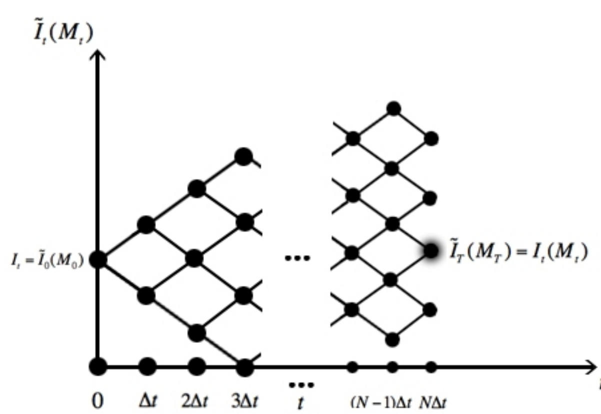
Graphically, by net investment there is then a mapping from the consumption choice to the evolution of health. Refer to Figure 2.

Figure 2



This illustrates how health might move dynamically across the illness episode. The darker paths indicate which nodes are feasible to ultimately achieve health H^* to leave the individual back in long-run equilibrium. It is possible, such as the case of chronic illness, that the original H^* can never be achieved. The research question is only concerned with whether a person's consumption settles over time into a long-run equilibrium, a steady state captured by larger time steps.

Figure 3



The model as outlined is indifferent to such an outcome, and it is acceptable from the theorist and econometrician's standpoint that the new equilibrium is different from the original steady state. This is because the model is concerned primarily with the health investment function $I(M_t)$ eventually reaching a long-run steady state. Refer to Figure 3. No matter what the level of long-run health H^* happens to be, when adjustment of the portfolio stops the individual is back in a long-run equilibrium and the short-run analysis may end. The next section outlines the empirical strategy for assessing these optimal investment choices in the data.

IV. The Empirical Strategy and Data

Uncertainty over health stock, prices, and the effectiveness of care necessitates sequential reassessments of one's demand throughout the episode. As outlined, at each point in time the utility maximizing consumer updates quantities in the health input portfolio until marginal benefit equates to marginal cost. We are interested in understanding how consumers make these sequential, dynamic choices, given that the patient and physician update based on recent information from previous attempts at treatment. Hence, the theoretical story is about quantities in a portfolio vector.

The empiricist is unable to differentiate between relevant quantities, however, since he only observes whether or not the individual visited the doctor. There is no uniform assessment of the intensity of a particular visit in the data. Is an outpatient visit worth more quantitatively than an office visit? How do ER visits compare to inpatient stays? In a theoretical sense, the "intensity" of treatment implicitly defines a "quantity" for the consumer, but consistent assessment of that quantity is elusive for the econometrician. The empirical story, then, is of discrete choice to consume or not consume within a time period.

This paper adopts a probabilistic approach to estimating these choices[21]. Since the decision tree model generates a stochastic bridge for the evolution of underlying health stock, the theory guarantees that for each choice to consume there is an equivalent probability describing that choice. The empirical strategy, then, is to estimate this probability at each node of the tree.

The Data

To test the theoretical model, this paper's empirical exercise focuses on illness episodes beginning with heart attacks, ischemic heart conditions, or other general severe shocks to health related to the heart. Examining illness episodes related to heart conditions is advantageous for three reasons. First, they are expensive and fearsome, and are thus non-trivial threats to the consumer's long-run health equilibrium. Second, treatment is generally comparable across individuals but also maintains an unavoidable random

[21] It is also chosen to avoid the complications caused by zero-inflated expenditures.

component in the treatment's effectiveness. Finally, the episodes are well defined. ICD-9 diagnosis codes related to the conditions are easily identified, and the length of the episodes are regarded in the literature to last 90 days to complete primary treatment[22].

The data used are panels 8-10 (2003-2006) of the Medical Expenditure Panel Survey (MEPS). MEPS began in 1996 and is an ongoing survey in which each panel follows roughly 15,000 individuals over two year periods. Data are collected in five rounds over the sample period, or every 5 months. MEPS was chosen because it has detailed medical event data for a large number of individuals. Panels 8-10 were chosen for the sake of variable uniformity caused by MEPS design, as well as to narrow the window of medical expenditure inflation.

The heart conditions sample was constructed as follows. All inpatient, outpatient, ER, and office based medical provider events for panels 8-10 were linked to medical conditions data and to demographics data for each individual. The time aggregated (year, round, month) data includes demographics, income[23], insurance converge, as well as various measures of health status. Panels 8-10 yielded approximately 45,000 individuals across 555,000 medical event observations.

Using ICD-9 diagnosis codes recorded at each medical event, all heart attacks, ischemic conditions, and generally severe heart problems were flagged as potential start points of the illness episode. The flagged list was further narrowed to only include hospitalization events[24]. Of these hospitalizations, the earliest was identified as the actual start of the illness episode. Next, all medical events within a 91 day window of the episode start date were identified as being within the primary-care illness episode commonly used by the literature. A small fraction of individuals had incomplete responses for key variables, such as source of payment or race, and were thrown out of the sample. This yielded a final sample of $1,803$ individuals with $19,715$ events. Four key variables were further defined for analysis: price, health status, $\triangle t$, and the dependent consumption variable.

Determining $\triangle t$

After a shock, the relevant time step dividing the tree's decision nodes is the length of time over which health portfolio inputs are relatively fixed. In the introduction's heart attack patient example, if $\triangle t = 1wk$ then each week the patient and physician assess health stock and the effectiveness and price of previous care and then adjust treatment

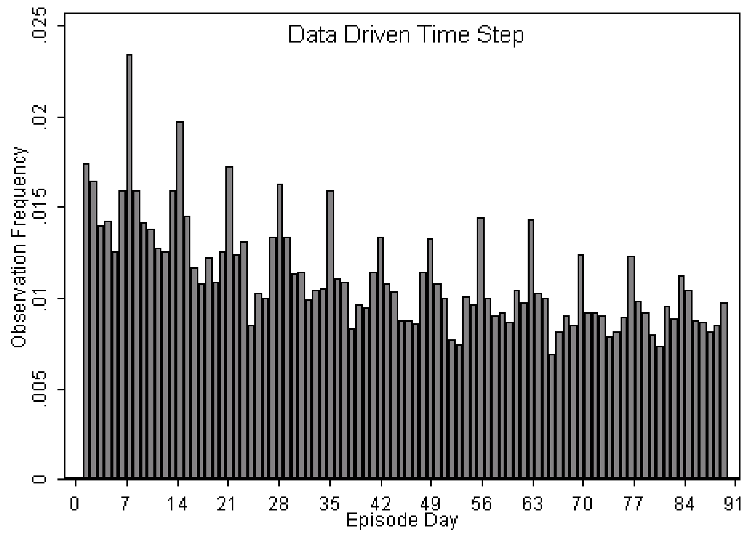
[22] 90 days is considered the appropriate time frame to capture primary treatment for the heart condition, such as surgery and initial physical therapy, while also avoiding treatment for various complications due to the shock. For example, see Cutler, McClellan, and Newhouse (2000).

[23] Annual income is not included in the regressions due to invariance across the illness episode. It is assumed that insurance coverage will capture necessary income effects.

[24] To maintain the notion of a severe shock.

accordingly. The appropriate time step $\triangle t$ for the decision tree was uncovered from the heart episode sample by examining the day-to-day frequency of medical care events within the episode. The histogram in Figure 4 is the daily distribution of medical events across the episode. It revealed that individuals, on average, fix their health portfolio choices on a week-to-week basis[25].

Figure 4



The Dependent Variable

With $\triangle t = 1wk$ set, consumption is assumed to occur on a week-to-week basis. The dependent variable was coded as 1 if the individual consumed medical care in a given week, and 0 if not. There are potential weaknesses of the dependent variable that should be noted. For instance, visits may be bundled together early on in the episode and scheduled in advance. There is also the possibility of an unobservable marginal product of medical care from week-to-week, and even the ability for the consumer to update demand without a visit. These are not accounted for in the data [26].

[25] The start of the episode, day 0, is omitted for the sake of scaling. There is also evidence in the data that the week-to-week $\triangle t$ holds for longer than the 91 day period. There is a structural break in frequency of care around the 13th week, however, evidencing the choice for the length of the illness episode. This is discussed in the data appendix, Appendix B.

[26] Some possibilities include the following. First, empirically some medical visits are scheduled in advance without consideration to current information or need, and are thus not generated from the assess-and-update decision theory as proposed. For instance, a physician may schedule a checkup one month after a surgery; and this would not be a week-to-week decision. Second, the marginal product of some medical treatments may not be fully observed after only one week. In this case, it is assumed that the physician and patient make choices in line with the treatment's expected marginal product based the most information available. Finally, it is possible no visit is needed to assess health stock and update demand, and the data will not observe an adjustment. For example, a consumer and physician

The variable's construction is in line with the probabilistic approach to measuring consumption this paper adopts. As already outlined, such an approach is motivated to avoid complications in measuring "quantity" and also to prevent complications caused by zero-inflation of the dependent variable. The {0,1} measure aggregates the week-level portfolio of health inputs, and a change from 0 to 1, or 1 to 0, occurs with the consumer's assessment of week level prices and week level health status. To control for individuals who die during the episode, once dead they are removed from the sample for the weeks following death.

The Price Variable

Price is measured as the per-visit running average out-of-pocket expense; throughout the episode $P_{m,t} = \frac{\sum OOP_t}{\sum M_t}$. This means average expenses in, for instance, week 4 are affected by previous weeks' prices and quantities. Another potential measure of price is the weekly per-visit average out-of-pocket expense, rather than the running average. The running average measure of price was motivated by the analysis below, largely since it is close to the cost measure of interest in the theoretical decision tree. However, for robustness the model was tested using the alternative price measure and the results were unaltered.

Determining the appropriate price is difficult since individuals are both forward looking and often billed *ex post* for treatment. Even when they are not billed *ex post* they are generally concerned with the total expense of their treatment over an episode, and not just the immediate choice. Furthermore, insurance often includes out-of-pocket maximums and deductibles. If an individual is near his deductible, his average out-of-pocket cost will not equal the marginal cost of care since he accounts for the impact of the deductible on future consumption.

When present, deductibles create a non-linear price schedule in which price is a function of quantity. Hence, out-of-pocket prices are endogenous to the choice to consume care, and using purely retrospective or average prices for a period can lead to biased results. For instance, Keeler, Newhouse, and Phelps (1977) consider the consumption of health care for individuals nearing their insurance deductible within a period. When uncertainty over health status is introduced into their model the deductibles induce non-linear price schedules over the entire illness episode.

For these reasons, Ellis (1986) argues that expected end-of-year or end-of-episode prices are the theoretically appropriate price measure. Following Ellis (1986), studies

might weigh treatment options over the telephone. In this case, the dependent variables as coded will underestimate the quantity consumers actually demanded.

often proxy expected end-of-period prices in their estimation using a two-stage model treating average out-of-pocket costs as endogenous and instrumenting the expected out-of-pocket cost using insurance coverage. Insurance coverage is viewed as the option to access a particular non-linear price schedule for medical care. This paper follows previous research and uses insurance coverage as instruments. When accounting for non-linear price schedules, on a week-to-week basis the predicted change in average cost should approximate the per-unit marginal cost of additional medical care consumed at the decision node.

Admittedly, in the long-run individuals who expect to consume more care are thus more likely to fully insure[27]. In lifetime steady state, then, the insurance choice is also endogenous to the consumption choice. However, if coverage is fixed in the short run, which is supported by the data, then the quantity effect of insurance is negligible over the adjustment period. Consumers are not capable of switching contacts to reflect increased illness episode care. Hence, using insurance coverage in the short-run as an instrument is valuable since it is difficult to imagine ways that coverage, essentially the option to purchase care at a set price, would affect the choice to consume in ways other than through the price itself. The empirical strength of insurance status as an instrument is supported by the data; this addressed later in the results section.

Measuring Health Status

Since a direct event level measure of health status is not available, weekly health status is constructed using weekly ICD-9 diagnosis codes and the individual's annual health score provided by MEPS. The annual health score ranges on $[0, 100]$ and is computed by MEPS taking many facets of the individual's health into account[28]. ICD-9 codes are available for each medical event, however, which does reveal significant information about the individual's health status at each point in time. The challenge is to convert weekly ICD-9 codes into a uniform, comparable measure of health status[29]. The method used to construct the variable is as follows.

All ICD-9 primary codes diagnosed for an individual within the year were examined to obtain the 40 most common codes in the data[30], excluding uninformative codes such

[27]This is essentially adverse selection in health insurance markets, and the literature exploring its existence is large. See Rothschild and Stiglitz (1976) for an early theoretical treatment.

[28]e.g. ADL flags, medical events and conditions, and demographics.

[29]This author recognizes that such a constructed measure of health status is less than ideal. However, the intent of the measure is to have a consistent update of health stock throughout the episode. The ICD-9 diagnoses do hold consistent information on heterogeneous inflictions. Any consistent, order-preserving mapping of these codes to a health level will maintain all of the needed information contained in the code.

[30]Forty codes is not an immediately intuitive cutoff. It was chosen examining frequency of codes across

as “undefined illness.” These 40 codes, which account for more than 53% of events in the sample, were converted into indicator variables: 1 if the individual was diagnosed, 0 otherwise. Annual health scores were then regressed on the yearly ICD-9 indicator variables; insignificant codes were thrown out sequentially until remaining ICD-9 codes were either indicators of heart disease and/or significant at the 10% level using heteroscedasticity robust standard errors. There were 22 codes in the final annual health score regression; the results of this regression appear in Appendix B. Variation in these 22 codes explained 10% of the variation in the annual health score.

Next, ICD-9 indicators were created at the week level using ICD-9 diagnosis for each individual in each week. The coefficients of the annual health score regression were then used to predict week-level health scores based on these week-level ICD-9 data. This health score is the model’s measure of week-to-week evolving health status.

Since “health status” depends on new ICD-9 codes to change each week, individuals not consuming care are assigned the previous week’s health status. That is, health status is only updated when new information is available. This is arguably consistent with real life, where individuals do not fully know their own health status until examined by a doctor. However, it also may introduce a positive update bias in the regression models.

Figure 5

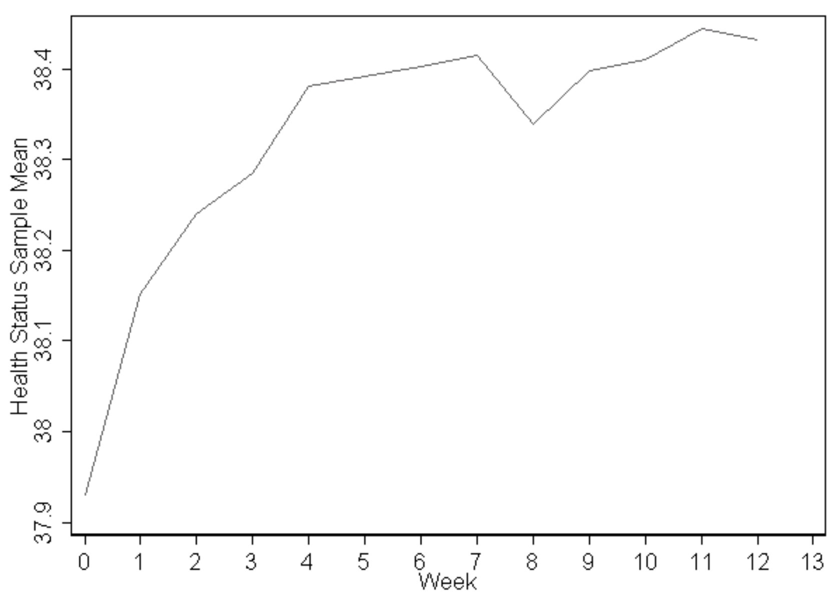


Figure 5 above shows the evolution of sample mean health stock over the episode.

medical events. Hundreds of ICD-9 codes appear in the data, but most have extremely low frequency (e.g. less than .1% of events). Being very generous with an initial definition high frequency (at least 1% of the events must have recorded the code), just over forty codes appeared most often, and when uninformative codes such as “undefined illness” were ignored only forty codes remained.

Remarkably, it should be noted that the health stock measure appears theoretically consistent with the notion of convergence to long-run health H^* by the end of the episode. However, the (in)variation of the constructed variable should be noted.

Table 1 provides descriptive statistics for the sample as well as weekly summaries of average out-of-pocket expenditures, running average out-of-pocket price, and health status. Refer to Table 1. Prices are relatively stable throughout the period but fall as the episode progresses. This likely reflects individuals reaching their out-of-pocket maximums as a result of insurance coverage. It should also be noted that mean health status grows over the episode, as a result of investment in health, but not over a wide range of values. This is likely due to the constructed nature of the variable, since the ICD-9 codes used only explain 10% of the variation in long-run health levels.

The cumulative mean number of ICD-9 codes diagnosed increases over the course of the episode. This is consistent with the hypothesis that medical care has random effectiveness and that additional shocks to health might occur during the adjustment to long-run steady state, since both sources of uncertainty require new ICD-9 diagnoses. Mean education is just below high school graduate. Fewer men are in the sample than women. 52% of the sample is covered by private insurance, 53% by Medicare, 20% by Medicaid, and 8% are uninsured. Whites represent 77% of the sample. The mean annual income is $23,545 but the standard error is quite large. Mean age is 62 and age ranges from 18 to 85 in the sample. A summary of the dependent variable is left for the results tables for ease of reference to the marginal probability estimates.

Table 1: Descriptive Statistics MEPS Panels 8-10 for Severe Heart Episodes

Sample Week	Wk0	Wk1	Wk2	Wk3	Wk4	Wk5	Wk6	Wk7	Wk8	Wk9	Wk10	Wk11	Wk12
Weekly Ave OOP	29.52 (145.90)	12.56 (108.49)	9.95 (112.55)	6.91 (32.31)	6.09 (33.98)	5.41 (37.02)	7.41 (63.31)	4.04 (22.33)	8.99 (170.98)	4.93 (40.50)	6.71 (72.77)	5.84 (57.51)	3.91 (22.43)
Running Ave OOP (RAP) [a]	29.52 (145.90)	27.71 (135.60)	26.19 (128.70)	25.23 (126.20)	23.97 (112.50)	23.23 (108.50)	23.10 (107.20)	22.52 (105.30)	22.61 (104.70)	21.40 (83.24)	21.39 (82.69)	21.20 (81.78)	20.79 (78.89)
RAP w/ Private Ins	29.76 (109.30)	28.79 (105.78)	26.02 (88.89)	25.42 (88.16)	24.65 (81.39)	24.09 (80.15)	24.19 (80.34)	23.47 (76.83)	23.20 (75.80)	23.07 (75.34)	23.05 (73.73)	22.83 (72.95)	22.31 (68.59)
RAP w/ Medicare	12.85 (69.06)	14.22 (81.73)	13.69 (85.49)	13.81 (83.84)	13.07 (77.13)	12.19 (67.30)	12.01 (66.78)	11.51 (63.67)	11.61 (62.16)	11.71 (61.94)	11.38 (59.59)	11.22 (58.24)	10.90 (53.11)
RAP w/ Medicaid	4.91 (56.89)	5.41 (57.10)	4.32 (35.20)	4.23 (35.36)	4.04 (34.80)	3.57 (28.88)	3.74 (28.90)	3.71 (26.75)	3.77 (26.70)	3.62 (25.58)	3.39 (25.20)	3.72 (25.48)	3.55 (25.33)
Num ICD-9 Codes	3.23 (2.73)	4.52 (4.00)	5.64 (5.27)	6.68 (6.47)	7.71 (7.71)	8.66 (8.86)	9.54 (10.01)	10.38 (11.11)	11.29 (12.26)	12.11 (13.34)	12.93 (14.51)	13.73 (15.54)	14.52 (16.62)
Health Status	37.93 (2.90)	38.15 (2.65)	38.24 (2.52)	38.29 (2.49)	38.38 (2.44)	38.39 (2.40)	38.40 (2.42)	38.42 (2.39)	38.34 (2.47)	38.40 (2.44)	38.41 (2.44)	38.44 (2.38)	38.43 (2.41)

	Edu	Gender	Age	White	Black	Income	Married	Private Ins	Medicare	Medicaid	Uninsured
Demographics	11.90 (3.25)	0.40 (0.49)	61.89 (14.33)	0.77 (0.42)	0.18 (0.39)	23,545 (22,918)	0.52 (0.50)	0.52 (0.50)	0.53 (0.50)	0.20 (0.40)	0.08 (0.27)

Notes:
Mean is shown; St. Error in parenthesis
Sample N is 23,439; weekly N is 1803, not accounting for deaths. Sample is all inpatient, outpatient, office based, and ER medical visits in Panels 8-10 (2003-2006) of MEPS for individuals experiencing an illness episode (13 weeks) induced by heart attack or severe (e.g. ischemic) heart condition.
[a] The price measure for the later regressions.

Linear Probability Model for each $\triangle t$

Two models are run to assess the probability of consuming medical care on a week-to-week basis: three-stage least squares (3SLS) and dynamic three-stage least squares (D3SLS). The empirically observed "price" is potentially endogenous to the choice to consume, so a two-stage estimation is appropriate to control for the simultaneous choice. The 3SLS estimator uses the first stage's predicted price in a second stage linear probability model of the weekly consumption of medical care. The three stage estimator was used, despite only have two stages, to ensure the efficiency of the standard errors. The 3SLS estimator allows correlation in residuals and as well as in the standard errors of the the same covariates across regression stages.

The dynamic model, hereafter D3SLS, was chosen to capture the potential theoretically relevant dynamic adjustment of demand. The D3SLS regressions are the same as the 3SLS model, only a lagged dependent variable enters as an additional covariate. The D3SLS model also helps control for potential omitted variables effecting the consumer's decision via the inclusion of lagged consumption, this helps stabilize the linear probability predictions giving the model a better overall fit[31].

Typical demographics (race, age, marital status, education, etc.) are used as controls in each stage. Income is not used in the final specification because the only data available is annual income, this made it insignificant both statistically and economically throughout the regressions. Income was found to be correlated with insurance, in which case one may argue the use of insurance indicators to predict price will account for the income effect in the non-linear price schedule.

For comparison to traditional large time step studies, an annualized model of health care demand is estimated using 3SLS for the same sample's individuals over a pooled two-year period[32]. The annual model differs from the weekly regression only in that consumption is allowed to be continuous. This is done because zero-inflation was not an issue over the two year time span, rendering the linear probability models inapplicable.

[31] Special care must be taken in estimating models with lagged dependent variables. Potential issues are dependence of the regression error across periods and correlation of other covariates with the lagged variable. Short of complicating the econometrics of the paper considerably, these must be assumed minor issues. The 3SLS estimator may control for correlation between the lagged variable and other covariates, especially between stages of the regression model. However, it must still be assumed that the residuals are not correlated with the lagged dependent variables. This is likely an erroneous assumption, but it is made for ease of estimating the models.

[32] The annual sample is all medical care visits of the individuals' two year MEPS sample window. The two years were pooled to account for the fact that some illness episodes spanned two different years.

For the same reasons, a 3SLS model is used to estimate demand during the week immediately following the health shock (week 0). By sample construction, every individual consumed in the first week and the binary model was inappropriate.

Formally, the first stage for the t^{th} period price is:

$$\begin{aligned} \text{3SLS Stage 1: } \hat{P}_{m,t} &= E[P_{m,t}|H_{i,t}, X_{i,t}, I_{i,t}] = \beta_0 + \beta_1 H_{i,t} + \beta_2 X_{i,t} + \beta_3 I_{i,t} + \epsilon_{i,t} \\ \text{D3SLS Stage 1: } \hat{P}_{m,t} &= E[P_{m,t}|H_{i,t}, X_{i,t}, I_{i,t}] = \beta_0 + \beta_1 H_{i,t} + \beta_2 X_{i,t} + \beta_3 I_{i,t} + \beta_4 Y_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{7}$$

where $E[\cdot]$ denotes the expectation, $P_{m,t}$ is the per-visit average out-of-pocket costs up to and including period t, $I_{i,t}$ is the instrument vector of insurance status indicators (Medicare, Medicaid, and Private Insurance), H_t is the health stock measure, $X_{i,t}$ is a vector of demographic controls, and $\epsilon_{i,t}$ is an error term. $\hat{P}_{m,t}$ is predicted and included in a second stage to estimate the probability of medical care consumption in period t. The second stage is assumed to be a function of expected marginal cost, health status, and demographics. Formally, the second stage is:

$$\begin{aligned} \text{3SLS Stage 2: } Prob[Y_{i,t}|H_{i,t}, X_{i,t}] &= \beta_0 + \beta_1 H_{i,t} + \beta_2 X_{i,t} + \beta_3 \hat{P}_{m,t} + \mu_{i,t} \\ \text{D3SLS Stage 2: } Prob[Y_{i,t}|H_{i,t}, X_{i,t}] &= \beta_0 + \beta_1 H_{i,t} + \beta_2 X_{i,t} + \beta_3 \hat{P}_{m,t} + \beta_4 Y_{i,t-1} + \mu_{i,t} \end{aligned} \tag{8}$$

where $\mu_{i,t}$ is an error term and the other regressors are defined as in stage 1. It is expected that invariance in the demographics reduces their added value in the regressions. However, they provide a nice benchmark against previous research as well as stabilize the regressions, and are thus kept for the analysis.

For the week level models other specifications, including fixed effects, were tried and rejected for two reasons. First, the theoretical model speculates that the coefficients are time dependent. Models that violated the time dependence of the β coefficients were not used in final analysis. In the case of fixed effects, if the βs are not time independent then the estimates will be an oddly weighted combination of the true β_t's that is much larger than a consistent estimate of β_t.

The results of the fixed effects models indeed showed large coefficients, ten times the size of the regular 3SLS models. These appear in the results appendix. The elasticities predicted using the fixed effects specification were too large to be believable given previous literature, and in many cases had positive signs.

Second, an F test of the null hypothesis that all the fixed effects are jointly zero ($v_i = 0 \, \forall i$) was run and the null could not be rejected in all but one weekly model (p values very close to 1 throughout the episode). The same F test was run on the pooled episode observations to see if the two period comparisons biased the results. Again, the p value of the F test was near 1 and the null could not be rejected.

For robustness, both the 3SLS and D3SLS specifications were tested on a sample in which the dependent variable was subject to an expenditure threshold. Positive consumption was recoded as zero if the total expense of the medical care (not just the out-of-pocket cost) was below the week's sample median. This was done primarily to avoid potential "false positives" for consumption that were, in reality, only trivial checkup visits. The threshold also may help control for spurious correlation between the dependent variable and the health status measure, as the health measure is updated only when the individual consumes care. Since nearly 50% of those with updated health have their dependent variable recoded as zero due to low total expenditure, the update bias is lessened or removed.

V. Results and Discussion

To provide context for the week-level models in reference to normal methods, Table 2 provides 3SLS results of the models at the annual level as well as for the first week of the illness episode (week 0). The results of Table 2 are the consumer's long-run estimates of demand. That is, demand over large time steps. Refer to Table 2. Note that price is negative and statistically significant in both regressions. Health status is negative and significant as well. This is in line with previous research that health and medical care consumption are negatively correlated. Many of the demographic variables are insignificant in the second stage of both models. As will be seen, the same trend holds for the weekly regressions.

Education is positive and significant in both models. A possible explanation is that more educated individuals are more efficient consumers of medical care. The sign and significance is in accord with previous research. The coefficient on price is extremely small relative to the magnitude of the average expenditures. The mean predicted price elasticities affirm this result. For the annualized model, the mean elasticity is -0.52. For the first week of the episode it is -0.14. Previous elasticity estimates are often in the range of -0.2, implying this sample is not unusual from those previously studied.

F-statistics assessed the joint significance of the instruments. Each was well over 10, implying that the instruments are both relevant and strong. It should be noted that the F-statistics are much larger during the illness episode compared to the annual model. This supports the hypothesis that the potential endogeneity of insurance coverage is not an issue during the short-run adjustment problem.

Table 2: 3SLS Demand Estimates for Large Time Step & 1st Week of Episode

	Demand over 2 Years		Demand In 1st Week	
	2nd Stage [a]	1st Stage	2nd Stage	1st Stage
Average Price	-0.048*** (0.011)		-0.008*** (0.002)	
Age	0.123 (0.278)	6.311** (2.769)	0.019 (0.026)	3.096* (1.783)
Age Squared	-0.001 (0.002)	-0.043* (0.023)	0.000 (0.000)	-0.02 (0.015)
Gender	-1.831* (1.110)	24.155** (11.117)	-0.134 (0.100)	4.331 (7.161)
Married	-0.778 (1.096)	-24.994** (11.509)	0.059 (0.102)	9.508 (7.368)
White	3.669 (2.494)	-5.636 (25.748)	0.249 (0.236)	23.162 (16.584)
Black	0.615 (2.704)	3.178 (27.843)	0.039 (0.254)	21.62 (17.931)
Education	0.710*** (0.164)	-3.482** (1.755)	0.028* (0.015)	-0.115 (1.108)
Health Status [b]	-0.395*** (0.048)	-0.275 (0.506)	-0.159*** (0.018)	2.880** (1.175)
Private Insurance		-61.681*** (12.355)		-30.156*** (7.438)
Medicare		-36.913** (15.020)		-52.154*** (9.629)
Medicaid		-133.537*** (15.820)		-32.811*** (9.315)
Other Public Insurance		5.419 (23.861)		-32.288* (17.745)
Constant	27.066*** (8.667)	67.846 (90.606)	8.007*** (1.116)	-165.137** (73.419)

Note:
St. Error in parenthesis; significance levels are *** p<0.01, **p<0.05, and *p<0.1.
Sample is all inpatient, outpatient, office based, and ER medical visits in Panels 8-10 (2003-2006) of MEPS for individuals experiencing an illness episode (90 days) induced by heart attack or severe (e.g. ischemic) heart condition.
[a] Average out-of-pocket price is treated as endogenous due to nonlinear price schedule caused by deductibles and out-of-pocket maximums, instruments are insurance status indicators.
[b] Health status is a continuous measure on [0,100]. Year-level model uses the mean of actual annual health scores. 1st week is based on ICD-9 codes for conditions diagnosed at the medical event. It is derived by predicting the continuous annual health score supplied by MEPS using all annual ICD-9 codes, and then local week-level scores were computed using these coefficients and week-level ICD-9 diagnoses.

Weekly Regressions

Table 3 provides the results of the episode's week-to-week 3SLS linear probability regressions both for the full sample and for the expenditure threshold sample. Demographics and the coefficients from the first stage for each model are not reported, interested readers will find full results in Appendix C. Before beginning a general discussion of the results, exceptional model fit throughout the regressions should be noted. Model chi-squared statistics are universally significant, most at the 1% level.

Unfortunately, R^2 measures are inappropriate for two-stage models and there is no immediate indication of how much of the variation in probability is explained by raw variation in the covariates. A measure of explained variation is useful since the main independent variables, health stock and marginal price, are essentially the same as the structural parameters of the theoretical model. To obtain an alternative indication of the theoretical model's potential structural fit, one may consider the variation in the dependent variable explained by predicted marginal price and the remaining covariates. In this case, the R^2 values of the second stage regression is remarkably high for panel data models, often ranging between 23% and 50%. Though not a perfect measure, it does evidence the strength of the model's underlying intuition.

A brief discussion of the validity of the instruments at the weekly level is warranted. The appendix lists the results of the first stage regression in detail. The instruments[33] (Medicare, Medicaid, and Private Insurance coverage) in all weeks showed remarkable strength and were both economically and statistically significant in every model. Chi-squared tests, rather than F tests due to the three stage model estimator, were run to test the null hypothesis that the insurance instruments were jointly zero at each stage of the illness episode. In all weeks the equivalent F statistic was greater than 10, implying the null hypothesis that the instruments were jointly weak may be rejected. The week-to-week variation in insurance coverage is small, implying people are not adjusting their coverage during the episode. Together these findings evidence the relevance and validity of the instruments chosen for the 3SLS models.

Refer to Table 3. The coefficients of expected out-of-pocket marginal cost are significant and properly signed in all weekly full-sample models. Note that soon after the episode's start, the marginal effect of price quickly exhibits stability as the episode progresses. That is, the change or acceleration of the marginal probability of price goes to zero soon after the health shock. This may describe rapid adjustment into an "illness episode demand." If so, it directly evidences the theoretical prediction that the consumer's investment function during his adjustment path differs from time-aggregated analysis of health care demand.

It is also possible that the in-variation instead is a signal of new long-run stability. If so, it is surprising from a theoretical standpoint since the decision tree theory of short-run adjustment predicts that the underlying dynamics of demand will change throughout the episode and only later settle at long-run levels.

In support of the former interpretation, though not apparent from Table 3, there is a slight growing and settling trend in price effects beyond the significant digits presented.

[33]Note that the indicator for other public insurance had to be dropped from the weekly regressions due to weakness. It was strong in the annual regression, however, and is kept for that reason. For robustness it should be noted that the results are not effected by the inclusion/exclusion of this indicator.

Accounting for these changes, the absolute effect of price on the probability of consuming in any given week grows by over 60% from the episode's start to end. The absolute effect of price is more clearly described by weekly price elasticities, which are discussed later.

The threshold sample results in Table 3 reveal that the price coefficients are robust to the choice of sample. In most weeks, the threshold price coefficients have similar sign, magnitude, and significance as the full-sample estimates. Toward the end of the episode, however, this absolute similarity disappears. For instance, in week 12 the threshold coefficient is one third the size of the full sample's prediction. This likely is due to the definition of individuals "consuming" care in the threshold sample, i.e. no trivial visits, toward the end of the episode. For example, an individual without insurance might be more sensitive to marginal price as the cumulative cost of the episode rises, and this individual's consumption is more likely to pass the threshold test because of his price schedule.

Before addressing the health stock coefficients it is useful to apply the price marginal probabilities to make their interpretation concrete. For instance, in the episode's second week 52.4% of the sample, or 944 individuals, reassessed their health stock, the effectiveness and prices of their medicare treatment, and adjusted health care demand accordingly. By Table 3, a 1% increase in price would reduce the probability of consuming by 0.2%. Hence, if out-of-pocket costs hypothetically increased by 1% we expect only $.998 * .524 * 1803 = 942.88$ individuals to consume, meaning that on average one or two people who would have changed their demand will not. In week 8, 34% of the sample, or 613 people, consumed care. A 1% increase in expected out-of-pocket cost decreases the probability of consuming by 0.3%. If prices hypothetically rose by 1% we would only expect $.997 * .34 * 1803 = 611.18$ people to consume, meaning once again only two people do not invest in health where they otherwise would have.

These results describe an extreme but entirely realistic insensitivity to price during a severe illness episode. Consider our introductory example of the hypothetical consumer after his heart attack. Suppose his marginal price of consumption in week 8 is only $30 because he is near his insurance deductible. Increasing his expected marginal price to $30.30 is economically negligible, so it is reasonable that he only reduces his consumption by 0.2%.

Table 3: 3SLS Marginal Probabilities of Consuming Medical Care

	Full Sample			Expenditure Threshold [c]		
	Observed Probability	Average Price [a]	Health Status [b]	Observed Probability	Average Price [a]	Health Status [b]
Week 1	0.524	-0.002** (0.001)	0.002 (0.005)	0.176	-0.001 (0.001)	-0.010*** (0.004)
Week 2	0.455	-0.002*** (0.001)	-0.006 (0.005)	0.198	-0.002*** (0.001)	-0.010** (0.005)
Week 3	0.420	-0.002** (0.001)	-0.007 (0.005)	0.196	-0.002*** (0.001)	-0.013*** (0.005)
Week 4	0.411	-0.002*** (0.001)	-0.012** (0.005)	0.202	-0.001** (0.001)	-0.018*** (0.004)
Week 5	0.393	-0.002*** (0.001)	-0.015*** (0.006)	0.201	-0.002*** (0.001)	-0.017*** (0.005)
Week 6	0.373	-0.002** (0.001)	-0.021*** (0.005)	0.186	-0.001** (0.001)	-0.019*** (0.004)
Week 7	0.341	-0.002*** (0.001)	-0.019*** (0.005)	0.186	-0.002*** (0.001)	-0.014*** (0.005)
Week 8	0.367	-0.003*** (0.001)	-0.017*** (0.006)	0.196	-0.003*** (0.001)	-0.016*** (0.005)
Week 9	0.343	-0.002** (0.001)	-0.013** (0.005)	0.174	-0.001 (0.001)	-0.019*** (0.004)
Week 10	0.335	-0.003*** (0.001)	-0.017*** (0.05)	0.184	-0.002*** (0.001)	-0.013*** (0.004)
Week 11	0.336	-0.002** (0.001)	-0.020*** (0.005)	0.181	-0.001* (0.001)	-0.017*** (0.004)
Week 12	0.334	-0.003*** (0.001)	-0.019 (0.005)	0.179	-0.001* (0.001)	-0.023*** (0.004)

NOTE:
St. Error in parenthesis; significance levels are *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.
Sample is all inpatient, outpatient, office based, and ER medical visits in Panels 8-10 (2003-2006) of MEPS for individuals experiencing an illness episode (13 weeks) induced by heart attack or severe (e.g. ischemic) heart condition.
[a] Cumulative average out-of-pocket price is treated as endogenous due to nonlinear price schedule caused by deductibles and out-of-pocket maximums, instruments are insurance status indicators.
[b] Health status is a continuous measure on [0,100] based on ICD-9 codes for conditions diagnosed at the medical event. It is derived by predicting the continuous annual health score supplied by MEPS using all annual ICD-9 codes, and then local week-level scores were computed using these coefficients and week-level ICD-9 diagnoses.
[c] The expenditure threshold recodes as 0 the bottom 50% of total expenditure (not just out-of-pocket) for dependent variables arising from a single visit within the week.

A discussion of expectations for the health stock measure is warranted before presenting the 3SLS models in Table 3. The theoretical decision rule over health stock predicts that as the marginal benefit of consuming care increases, so too should the probability of consuming care. The theoretical model implies two important scenarios to consider for the sign of health stock in the regressions. First is a positive sign on health stock resulting from actual benefits of care. The results do not align with this theory, and would do so only if the health stock measure reflected the benefits of medical care and not the state of current health. This expectation relies on an instantaneous impact of medical care at the time of the medical event.

A second potential outcome is a negative sign on health stock explained by the individual's current health. If individuals are capable of perceiving their own health status, then the ICD-9 codes revealed at the medical care event signal health status already known to the individual. If this is so, then one would expect poor health status to induce a medical care event since that is when the marginal benefit of care is highest. This interpretation aligns with the results in all model specifications.

Refer once again to Table 3. Note that the health status measure fits well with theoretical expectations as well as past empirical observation. The marginal probabilities are negative and statistically significant in almost every week. Empirically, this aligns with previous research findings that health and medical care demand are negatively correlated.

Recall, however, that there is potential for positively signed update bias in the construction of the health stock measure. The threshold sample controls for update bias in the health measure and maintains the significance and negative sign of health stock. This evidences the hypothesis that consumers, with their physician, are capable of perceiving the expected marginal benefit of medical care in any given week. From the decision tree theory, then, the marginal benefit of consuming medical care is greater when an individual is less healthy. Consumers with lower health stock foresee the benefits of medical care outweighing the marginal cost of the investment, so they are more likely to consume.

It should be noted that the coefficients exhibit a pattern of periodic growth and decay over the course of the episode. As Figure 5 revealed, this pattern is *not* part of the underlying data at its mean. Hence, the statistically significant periodic result must be somehow driven by the typical consumer's dynamic choices to assess and update his demand. One direct explanation is that the model is observing the consumer's response to underlying uncertainty of health stock and the random effectiveness of medical care.

As in the case of prices, the results seem more reasonable when applied to the sample's probabilities. In week 8, 34% of the sample, or 613 people, consumed care and the marginal effect of health status was -0.017. Consider first the effect of a hypothetical random shock. If consumers' collective health stock fell randomly by 1% between weeks 7 and 8, then it is expected that on average 10 or 11 more people (.017*.34*1803) would have consumed care. Suppose next that a newly available medication prescribed in week 7 increases the marginal product of treatment by 10%. Then, on average, 105 people in the sample would assess their improved health stock and adjust demand to not consume care in week 8.

The absolute magnitude of the health coefficient is larger than the price effect. This implies that individuals are more concerned with improving their health stock than with the marginal price of the investment after a severe health shock. This makes intuitive sense if consumers are extremely risk averse, since convergence to lifetime utility maximizing steady state depends on increasing their current health.

It is also possible that the length of the adjustment episode itself imposes cost (e.g. Wagstaff, 1986). In this case, the marginal price estimate may not capture the full marginal cost of current care since consuming today saves money in the future. Without holding this full marginal cost constant in the regression, the effect may instead be captured by the health status measure. The potential for this bias cannot be ignored, though the dynamic model (D3SLS) in Table 4 should account for the potentially unobserved cost of time.

Table 4 provides results of the D3SLS model. The results are very similar to those of Table 3; the overall trends in price and the findings regarding health stock are repeated[34]. Refer to Table 4. Remarkably, the magnitudes of the price coefficients are insensitive to the introduction of lagged consumption. The most notable difference is found in the efficiency of the estimates; fewer price coefficients are statistically significant compared to Table 3.

Health status falls in absolute magnitude in both samples in Table 4, but the directional impact from Table 3 remains the same. One explanation is that lagged consumption captures much of the consumer's dynamic trade offs over the course of the episode. This includes the time cost of the adjustment period, as well as money saved in the future due to health investment in the present. As hypothesized in the discussion of Table 3, it is possible that the size of the health effect was due to the insufficiency of the marginal price estimate. With these "hidden" costs held constant through lagged consumption, health status looses absolute magnitude as expected.

[34]It is interesting to consider the consumer's expected long-run behavior based only on his short-run data. If the D3SLS model is viewed as a Koyck lag model, then in "equilibrium" the dynamics fade, hence $Y_t = Y_{t-1}$ and consumption $Y_t = \beta_0 + \beta_1 H_{i,t} + \beta_2 X_{i,t} + \beta_3 \hat{P}_{m,t} + \beta_4 Y_{i,t-1} + \mu_{i,t}$ becomes $(1-\beta_4)Y_t = \beta_0 + \beta_1 H_{i,t} + \beta_2 X_{i,t} + \beta_3 \hat{P}_{m,t} + \mu_{i,t}$. Thus, multiplying the coefficients by $\frac{1}{1-\beta_4}$ yields the long-run parameter. From Table 4, in weeks 11 and 12 $\frac{1}{1-\beta_4} \approx 1.56$. It should be noted that weighting the week elasticities by 1.56 gives an estimate closer, but still below, the estimate based on the annual model (.25 vs .31).

Table 4: 3SLS Dynamic Marginal Probabilities of Consuming Medical Care

	Full Sample				Expenditure Threshold [d]			
	Observed Prob	Average Price [a]	Health Status [b]	Lagged Dep Var [c]	Observed Prob	Average Price	Health Status	Lagged Dep Var
Week 1	0.524	-0.002** (0.001)	0.002 (0.005)	0.000 (0.000)	0.176	-0.001 (0.000)	-0.009** (0.004)	0.138*** (0.021)
Week 2	0.455	-0.002*** (0.001)	-0.005 (0.005)	0.187*** (0.026)	0.198	-0.002*** (0.001)	-0.007 (0.005)	0.283*** (0.029)
Week 3	0.420	-0.001 (0.001)	-0.005 (0.005)	0.254*** (0.025)	0.196	-0.001** (0.001)	-0.011*** (0.004)	0.296*** (0.024)
Week 4	0.411	-0.002** (0.001)	-0.012** (0.005)	0.234*** (0.027)	0.202	-0.001 (0.001)	-0.015*** (0.004)	0.277*** (0.025)
Week 5	0.393	-0.002** (0.001)	-0.010* (0.060)	0.251*** (0.025)	0.201	-0.001** (0.001)	-0.011*** (0.004)	0.293*** (0.024)
Week 6	0.373	-0.001* (0.001)	-0.017*** (0.005)	0.246*** (0.025)	0.186	-0.001 (0.001)	-0.016*** (0.004)	0.261*** (0.023)
Week 7	0.341	-0.002** (0.001)	-0.013*** (0.005)	0.273*** (0.026)	0.186	-0.002*** (0.001)	-0.009** (0.004)	0.303*** (0.027)
Week 8	0.367	-0.002*** (0.001)	-0.010* (0.005)	0.282*** (0.027)	0.196	-0.002*** (0.001)	-0.012*** (0.004)	0.288*** (0.026)
Week 9	0.343	-0.001 (0.001)	-0.009* (0.005)	0.297*** (0.024)	0.174	-0.000 (0.001)	-0.016*** (0.004)	0.306*** (0.023)
Week 10	0.335	-0.002*** (0.001)	-0.013** (0.005)	0.299*** (0.025)	0.184	-0.002*** (0.001)	-0.007* (0.004)	0.288*** (0.027)
Week 11	0.336	-0.001 (0.001)	-0.013*** (0.005)	0.360*** (0.023)	0.181	-0.001 (0.001)	-0.012*** (0.004)	0.319*** (0.023)
Week 12	0.334	-0.002** (0.001)	-0.010** (0.005)	0.362*** (0.025)	0.179	-0.001 (0.001)	-0.016*** (0.004)	0.293*** (0.024)

NOTE:
St. Error in parenthesis; significance levels are *** p<0.01, **p<0.05, and *p<0.1.
Sample is all inpatient, outpatient, office based, and ER medical visits in Panels 8-10 (2003-2006) of MEPS for individuals experiencing an illness episode (13 weeks) induced by heart attack or severe (e.g. ischemic) heart condition.
[a] Cumulative average out-of-pocket price is treated as endogenous due to nonlinear price schedule caused by deductibles and out-of-pocket maximums, instruments are insurance status indicators.
[b] Health status is a continuous measure on [0,100] based on ICD-9 codes for conditions diagnosed at the medical event. It is derived by predicting the continuous annual health score supplied by MEPS using all annual ICD-9 codes, and then local week-level scores were computed using these coefficients and week-level ICD-9 diagnoses.
[c] Lagged consumption, the dependant variable from the previous week.
[d] The expenditure threshold recodes as 0 the bottom 50% of total expenditure (not just out-of-pocket) for dependent variables arising from a single visit within the week.

Lagged consumption is highly significant and positively signed throughout the models[35]. An immediate explanation is that individuals consuming care in any given week have lower health stock, on average, than those not consuming care. Since the marginal product of the care is random, the probability that their stock remains lower might be

[35]With the exception of the first week of the full sample. This is because lagged consumption has no effect in the regression since everyone consumed during the first week. The threshold sample allows inexpensive initial weeks to be coded as 0, so the measure has meaning in that model.

high. One might also expect a negative sign on the dynamic variable, since that would reflect the durability of health investments in the previous week. Medical care consumed today means less medical care is needed in the future. It is likely that these two directional effects, the illness effect (+) and the durability of health investment (-), compete in the regression. The results cannot de-tangle the magnitudes of each. However, Table 4 does show that the illness effect clearly overwhelms any negative pressure future savings might put on the coefficient.

The dominance of the illness effect is even clearer when false-positives are controlled for in the sample. In the threshold regressions, lagged consumption is large, positive, and statistically significant in all weeks. For a consumer in any given period it implies that non-trivial consumption last week increases the likelihood of non-trivial consumption this week. Unobserved variables, which are partially captured by lagged consumption, may also be driving this result. In this case one need only view the results of Table 4 as more robust variations of Table 3.

Elasticities

It is interesting to consider the price and health elasticities of demand throughout the episode. Figure 6 graphs the mean predicted price elasticity over the course of the episode for each model specification and sample. The mean of the inter-80% range was used to avoid the effect of outliers caused by the linear probability model[36].

The price elasticities appear relatively stable, but an overall increasing trend is clear. Interestingly, they also exhibit the same periodic growth and decay observed in the health status variable results from Table 3 and Table 4. Compared to his long-run price elasticities[37], the average consumer is less sensitive to price immediately following the severe health shock. The annual model predicts the mean price elasticity is .31; the weekly models show values from .9 to .16 (both are mean within 80% range of predictions). This sensitivity grows over the course of the episode, increasing by over 60%. It is not clear, though, whether it eventually settles near long-run levels. The short-run inelastic difference is likely due to the unavailability of substitutes for particular medical care inputs, or for medical care itself, compared to long-run options.

The long-run elasticities fit with the findings of previous literature based on annual medical care demand, for example the RAND Health Insurance Experiment[38]. The fact that elasticities during the illness episode are substantially different from their long-run

[36]This range was chosen because it was the largest range over which the mean appeared stable.

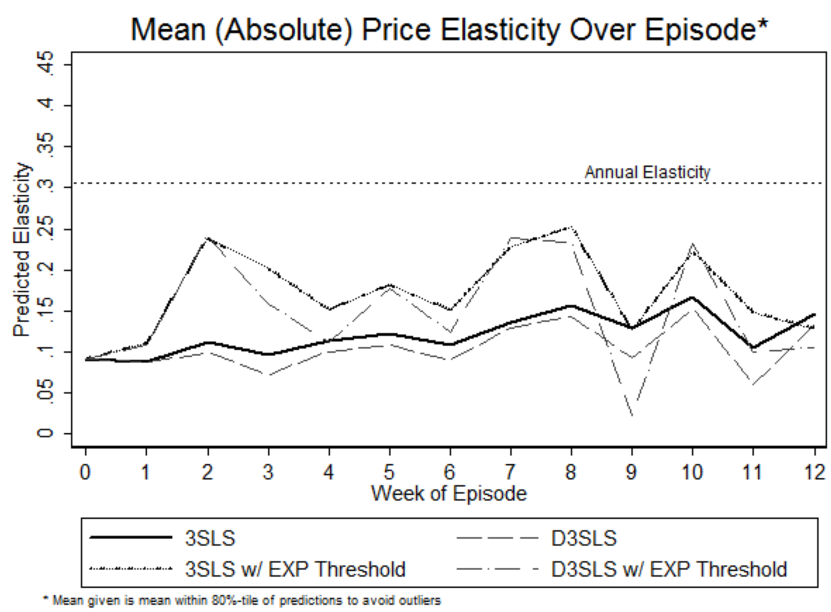
[37]To be clear, long-run here refers to estimates from the annual regressions, which are assumed to reflect long-run steady state.

[38]The RHIE found price elasticities around -0.2.

counterpart clearly evidences the importance of studying demand along the short-run adjustment path. The trend and general size of the predicted elasticity is invariant to the model specification, 3SLS versus D3SLS, but is slightly larger in absolute magnitude for the threshold sample. This evidences the notion that consumers with less insurance coverage, and thus a higher price schedule, are more price sensitive. The implications of this are discussed shortly.

Though the picture is convincing, t-tests on the difference between the mean weekly estimate and the mean long-run estimate were run to formally test the results. In each week, all estimates were significantly different from the long-run mean at either the 99% or 95% level. The statistically significant difference is particularly pronounced for the non-threshold sample. The t-test results affirm the insights of Figure 6.

Figure 6

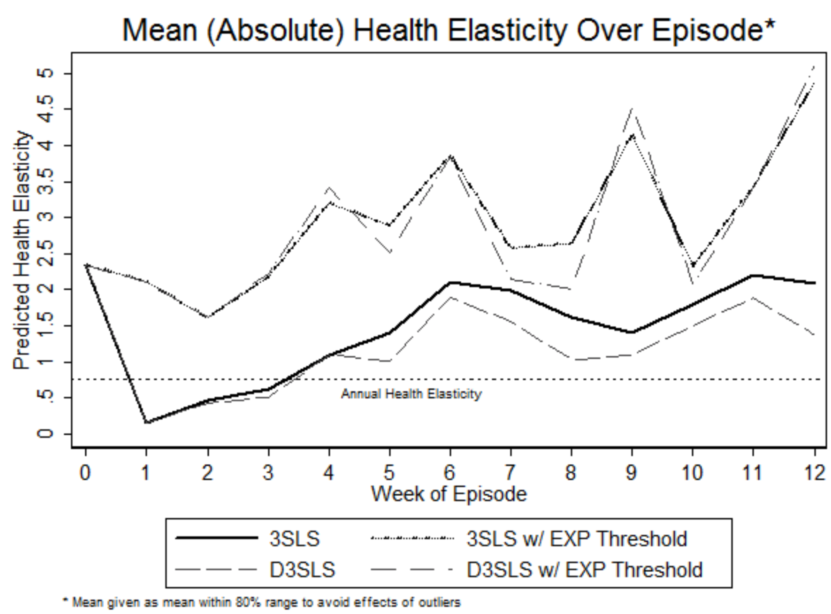


The demand curve's implied elasticity of latent health stock is also of interest. It should be noted that, to the knowledge of this author, no previous estimate exists of health stock elasticity of medical care demand. Refer to Figure 7. The responsiveness of demand to underlying changes in health is much larger than the price elasticity. Indeed, it is almost universally greater than one. This implies that, unlike price, demand is elastic to expected changes in health stock, such as shocks to health or increased marginal product of medical care.

There are two ways to interpret the elasticity. The first is as a predictor of expected marginal product of care. In this case, an increased marginal product of medical care means that consumers are able to decrease demand by more than their expected increase in health. The second and more important interpretation is that health stock is a latent variable. In this context, a negative elasticity (absolute elasticities are shown in the table) implies that consumer are willing to increase demand to maintain health stock *after* observing a decrease in their health. This is perhaps a more reasonable interpretation given the dynamic updating prediction of this study's theory section.

The overall trend of the elasticities over time is also striking. Soon after the health shock the health elasticities are smaller in absolute magnitude but begin to grow over time. The upward trend is more pronounced in the expenditure threshold sample predictions, as is a periodic behavior similar to that found in the price elasticities. The extreme difference between short and long-run health stock elasticities should also be noted. Steady state elasticity is less than 1. As with price, weekly t-tests confirm that the health elasticity during the illness episode is significantly different from the long-run steady state measure.

Figure 7



Discussion

The results of Tables 3 and 4, as well as the elasticities predicted by the models, support the notion that consumers demand medical care dynamically during an illness episode in ways that differ from their long-run steady state demand. The robustness of the results evidences the intuition of the theoretical model. However, the results also have powerful implications for the consumer's welfare. It is worthwhile to consider these implications before concluding the paper

First, and perhaps trivially, price sensitivity in the short and long-run have direct implications for efficiency. The results show that the timing of a price change may be of equal importance to the size of the price change for an individual during the illness episode. Consumers in the middle of adjustment after a shock are affected far more by price than consumers in steady state. This has direct implications for policy, since any change in price schedule, for instance through Medicare, will effect welfare in ways that cannot be fully captured by long-run estimates of medical care demand[39].

Secondly, and more importantly, the dynamics of demand over the adjustment path can explain propensity to adopt new medical technology. During a catastrophic illness episode, it is likely that the consumer's fear of death or disability might more strongly influence demand decisions than when the individual does not face impending doom. In such a situation, the use of sophisticated medical care is widely regarded as the primary source of price increases. The results of this study reveal that the incentives to utilize expensive technological care differ in the short-run versus the individual's long-run steady state.

Risk averse patients desire the care, and profit maximizing doctors and hospitals are only capable of incorporating more sophisticated treatments if the demand curve can absorb the increase in price. However, because demand elasticities are steeper after a health shock, the ability of the average consumer to absorb increased prices is understated by his long-run elasticity. Hence, when medical care suppliers exploit this inelasticity, or alternatively if they are completely benevolent and give in to the pressures of their patients, then this study's short-run elasticity results help explain the rapid adoption of medical technology and the price increases that accompany it.

To make this concrete, consider once again our hypothetical heart attack patient when faced with a simultaneous drop in health and increase in price. Suppose that during week 6 of the adjustment episode his health stock falls by 1%, perhaps due to ineffective treatment. In week 7, he and his physician assess this change and devise a new set of treatments to update his health investment portfolio. Holding the marginal cost of the portfolio fixed, the results show he is willing to increase demand by 2% to account for his lower health state.

Suppose that at the same time the doctor offers an expensive new medication that

[39]However, prices are likely stable throughout a short illness episode, so such efficiency concerns may be unwarranted.

may better meet the consumer's needs. Since the patient is price inelastic in week 7, a 1% increase in price only decreases demand by .1%. Therefore, the cost of the new medication must increase the marginal price of the health investment portfolio by more than 20%[40] before the patient is unwilling to make the investment and use the medication.

For comparison, if long-run estimates of the same parameters were used, a 1% increase in cost decreases quantity demanded by .3% and a 1% decrease in health increases quantity demanded by .75%. Thus, the cost of the new medication need only increase marginal price by 2.5% before the consumer will not accept the new treatment. Clearly, in ignoring these short-run dynamics past empirical explanations of rising costs must be questioned.

The results finally have implications for expenditure risk and insurance. Feldstein (1973) argues that the adoption of sophisticated standards of care increases the price of care for everyone. As prices rise, individuals are enticed to more fully insure against increased expenditure risk. Yet, as consumers are more fully insured, the cost of utilizing sophisticated care is lowered and hence consumers are more likely to consume. The cycle then repeats. Feldstein finds that welfare lost to increased prices in the cycle more than outweighs the welfare gained by reduced risk. Hence, the market settles at an over-insured equilibrium[41][42].

Explaining the rapid acceleration of health care costs and adoption of expensive medical technology is key to understanding these dynamics. In general, studies finding welfare loss and non-optimality in equilibrium are sensitive to two underlying parameters: price responsiveness of demand and risk aversion of consumers[43]. Yet, in each case the param-

[40] i.e. where quantity demanded increased due to health equals quantity demanded decreased due to price.

[41] Feldman and Dowd (1991) use Rand Health Insurance Experiment price elasticities and risk aversion measures to find that the welfare loss may be even higher than Feldstein imagined.

[42] Other pertinent analysis of expenditure risk and insurance considers the choices made to hedge against catastrophic illness episodes. Pauly (1974) opens the door for market failure in the case of catastrophic care, largely due to prevailing imperfect information in health care markets. Besley (1989) argues that optimal catastrophic insurance coverage does not exist without government intervention. This is largely because public provision of catastrophic care insurance might reduce the inefficiency of provision by private firms. Selden (1993) argues the reverse, noting that Besley's solved model is unsustainable in equilibrium. Blomqvist and Johansson (1997) attempt to obtain more general results insensitive to less restrictive assumptions about health and utility states like those made by Selden (1993). In each case, the essential result remains clear: catastrophic illness episodes expose the consumer to greater risk that might not be optimally insured away. Hence, the question of optimal protection against expenditure risk caused by catastrophic illness is important to health economics because it directly informs public policy over provision of of insurance and medical care.

[43] For instance, Feldstein (1973) and Feldman and Dowd (1991)'s findings are due to the empirically observed high degree of risk aversion (Friedman 1974) that consumers exhibit when choosing insurance against health shock and consequent expenditure risk. They are also caused by the degree of price sensitivity, or lack thereof, of consumers when demand medical care (Feldstein, 1973) .

eters used are estimated using steady state demand for medical care.

This study has shown that the consumer is less sensitive to price during the adjustment, perhaps reflecting some degree of necessity in the health investment. Given this, long-run demand parameters will underestimate the welfare loss due to increased price at lower insurance levels. Expenditure risk could easily be higher in the short-run due to greater exposure of the individual's wealth to his uncertain underlying health stock. The literature's common notions of over-insurance in health care markets, and attached welfare implications, should be reconsidered in light of this potentially greater risk aversion. From the results of this paper, the market's equilibrium may, in fact, allocate the welfare maximizing level of insurance.

VI. Conclusion

In conclusion, this paper addressed a largely unanswered question in the literature: How do consumers make sequential, dynamic choices to consume medical care during episodes of acute or chronic illness. The question was motivated by the reality of human health, that people rarely know they are sick until already inflicted. Answering this question theoretically gave rise to a portfolio theory of health investment. It described individual choices to assess and adjust health inputs over a finite time period to achieve a long-run targeted health level. The theory gave clear utility maximizing choice rules for updating the consumer's demand for medical care after a health shock, as well as a decision tree to describe these sequential choices individuals make during the illness episode.

This, in turn, motivated a straightforward empirical exercise to test the model's predictions. The empirical exercise confirmed the model's intuition and compared the findings to those based on previous long-run methods. Admittedly, the results fall short of depicting convergence back to long-run steady state. However, the trend toward the steady state is evident in the elasticity estimates. Inferences about underlying structural parameters of the model also arose from the results, evidencing the theory's description of short-run dynamic demand for medical care. Since the responses to severe random shocks account for the majority of an individual's health expenses, knowing that those choices are made dynamically has important implications for policy and consumer welfare.

The empirical results quantify those differences. Consumers are less price elastic and more health elastic over their adjustment path. The theory and empirical predictions well describe the incentives governing the rapid adoption of sophisticated medical technology, the aggregate increase in cost that results, and the insurance levels consumers choose to hedge against expenditure risk. At the very least, the implications warrant inclusion for the short-run adjustment problem in future research.

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Appendix A: Health Capital Theory

Let the consumer holds preferences over health H_t and other consumption C_t. Health also allows the individual to produce income, for example through healthy time in which he can work. Future utility and income are discounted to present terms in the maximization problem using rates β and r respectively. The consumer's lifetime utility maximization problem is:

$$\max \sum_t \beta^t U(C_t, H_t) \tag{9}$$

s.t. $H_t = (1-\delta)H_{t-1} + I(M_t)$ and $C_t + P_t M_t = f(H_t)$ health and budget constraints.

$I(\cdot)$ is a continuous health investment function mapping an input M_t of medical care (e.g. physician care, prescription drugs, diet, exercise, etc.) to health stock; $I' > 0$ and $I'' < 0$ to reflect the increasing and complementary effects of medical care inputs on health. Though a vector formulation of M_t is more realistic, assume $M_t \in \mathbb{R}$ for simplicity. Note that the evolution of health stock is also continuous. P_t is the price of medical care. Income is given by $f(H_t)$ to reflect the dependence of income flow on health stock (e.g. $f(H_t) = y_t + \psi(H_t)$ where y_t is a basic level of income and ψ is income tied to health, such as healthy time to work). Assume $f(\cdot)$ is continuous, with $f' > 0$ and $f'' < 0$.

Define the lifetime discount of future income as

$$d_t \equiv \prod_{j=0}^{t-1} (1+r)^{-j}. \tag{10}$$

Note that $H_t - (1-\delta)H_{t-1} = I[M_t] \implies M_t = I^{-1}[H_t - (1-\delta)H_{t-1}] \equiv G[H_t - (1-\delta)H_{t-1}]$ for some $G \equiv I^{-1}$ since $I(\cdot)$ is continuous. Using these two relations we may combine the budget and health constraints into a single lifetime constraint:

$$\sum_t d_t(C_t + P_t G[H_t - (1-\delta)H_{t-1}]) = \sum_t d_t f(H_t). \tag{11}$$

The consumer's lifetime utility maximizing problem becomes:

$$\max \sum_t \beta^t U(C_t, H_t) \tag{12}$$

s.t. $\sum_t d_t(C_t + P_t G[H_t - (1-\delta)H_{t-1}]) = \sum_t d_t f(H_t)$.

In Lagrangian form, the problem is:

$$L = \sum_{t=1}^{n} \beta^t U(C_t, H_t) + \lambda \sum_{t=1}^{n} d_t (f(H_t) - C_t - P_t G[H_t - (1-\delta)H_{t-1}]). \quad (13)$$

Letting subscripts denote partial derivatives, the First Order Conditions for each period t are:

$$\beta^t U_{C_t} = \lambda d_t \quad (14)$$

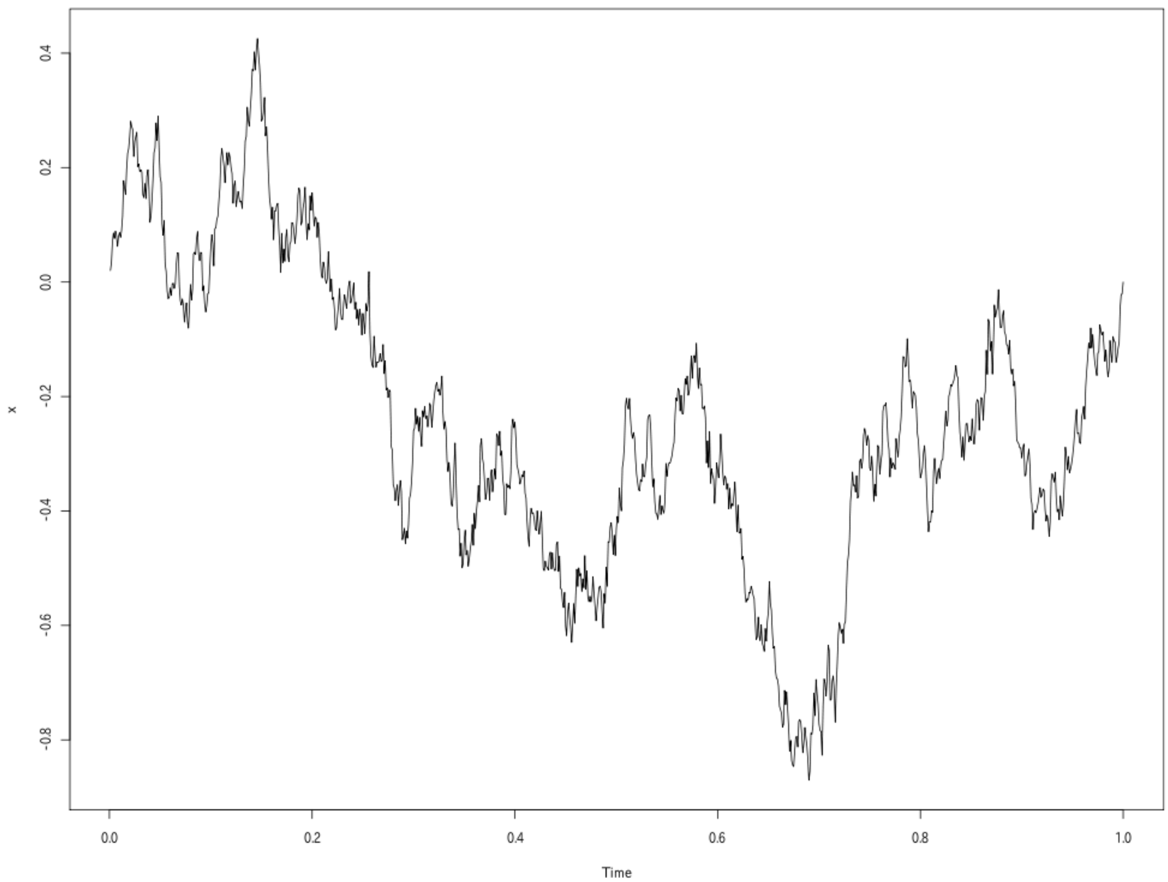
$$\beta^t U_{H_t} + \lambda d_t f'(H_t) - \lambda d_t P_t G'(H_t) + \lambda d_{t+1} P_{t+1}(1-\delta)G'(H_{t+1}) = 0. \quad (15)$$

(14) establishes the inter-temporal association between utility from consumption and its cost. For periods t and $t+1$ it states that $\frac{U_{C_t}}{1+r} = \beta U_{C_{t+1}}$, or present utility discounted at the cost of future consumption must equate to future utility discounted in utility terms. (15) states that the utility of health stock and the income it generates is proportional to the present net cost of the investment (cost in period t minus cost saved in period $t+1$). Grouping (14) and (15) establishes the utility maximizing conditions for investment in health stock:

$$\beta^t U_{H_t} + \beta^t U_{C_t} f'(H_t) - \beta^t U_{C_t} P_t G'(H_t) + \beta^{t+1} U_{C_{t+1}} P_{t+1}(1-\delta)G'(H_{t+1}) = 0. \quad (16)$$

In (16), M_t enters implicitly as the means of investing in health. Individuals invest in health until discounted marginal utility of health, as well as the additional consumption the income from health allows, equates to the discounted marginal net cost of the investment (discounted by consumption lost due to the marginal cost). M_t is consumed in accordance to these conditions. The result is a lifetime steady state consumption path for M_t and a lifetime optimal level of health stock $H*$ that the individual wishes to maintain.

An example of a stochastic bridge is the brownian bridge. A typical brownian bridge is below.

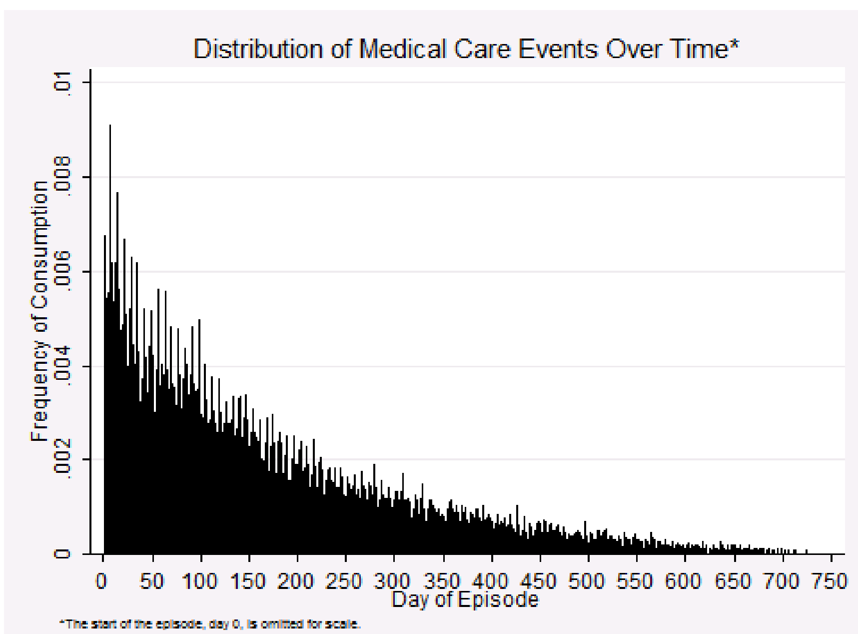

0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
x
0.0
0.2
0.4
0.6
0.8
1.0
Time

Appendix B: Data

This appendix discusses two variables of particular importance in the model: health status and the construction of $\triangle t$. The time step $\triangle t$ was pulled strait from the data by examining the daily density of medical care events across the 13 week period. The histogram in the text clearly showed that consumers on average consume in weekly time steps.

It was noted, though, that there is evidence that the one week time step continues past the 13 week period traditionally used in the analysis of heart conditions. The graph below shows the same daily density of medical care events over the two years following the start of the episode. Three things should be noted. First, not all individuals have two years of data after the start of their episode, the amount of time they are sampled depends on the timing of the episode within the MEPS sample window. Second, there is a clear structural break in the distribution of medical care events just before day 100, after which the weekly frequency is still apparent but much less so. This initial period is captured in the 13 week sample used in this study.

Third, approximately the next 110 days follow the less pronounced weekly pattern, it is possible that this is the continuation of the illness episode. If so, this may explain why demand elasticities did not converge to long-run levels by the end of the 13 weeks. An analysis of these later weeks was not conducted due to time constraints, the results of such an analysis are unknown.



The construction of health status is crucial to the results of this study. As described in the text, yearly MEPS health scores, a [0,100] measure, were predicted using yearly

ICD-9 codes. The 40 most common codes were converted to indicators to predict health status in a OLS regression with robust standard errors. Insignificant codes were thrown out sequentially until all 22 remaining codes were either statistically significant at the 90% level and/or were codes for the heart conditions used to identify the sample. The initial R^2 values with 30-40 codes were around .12, the 22 remaining codes yielded an R^2 of about .1. The regression output is below. These coefficients were used with the week level ICD-9 codes to predict weekly health status.

Appendix B Table 1: Health Status Construction Regression

ICD-9 Codes	Coef.	Robust Err.	t	P>t	95% Conf. Int	
icd_250	-3.884933	0.7810125	-4.97	0	-5.41679	-2.353075
icd_272	2.833531	1.159735	2.44	0.015	0.5588581	5.108204
icd_300	-3.287319	1.634809	-2.01	0.045	-6.493791	-0.080848
icd_311	-2.335912	1.386619	-1.68	0.092	-5.05559	0.3837671
icd_366	-2.003207	1.210035	-1.66	0.098	-4.376537	0.3701226
icd_401	1.296384	0.6382445	2.03	0.042	0.0445482	2.54822
icd_410	-0.3205312	1.33321	-0.24	0.81	-2.935454	2.294392
icd_414	-4.418555	1.641978	-2.69	0.007	-7.639088	-1.198022
icd_424	-2.948683	2.016091	-1.46	0.144	-6.90299	1.005625
icd_427	-1.276905	1.53867	-0.83	0.407	-4.294812	1.741002
icd_428	-7.066454	1.479292	-4.78	0	-9.967899	-4.16501
icd_429	-4.050793	1.365526	-2.97	0.003	-6.7291	-1.372485
icd_436	-4.985115	2.078093	-2.4	0.017	-9.061032	-0.909199
icd_444	0.2940642	1.70693	0.17	0.863	-3.053863	3.641991
icd_477	3.5644	2.004812	1.78	0.076	-0.367785	7.496586
icd_486	-6.908302	2.042918	-3.38	0.001	-10.91523	-2.901376
icd_493	-3.715255	1.874246	-1.98	0.048	-7.391351	-0.039159
icd_586	-9.526301	1.799902	-5.29	0	-13.05658	-5.99602
icd_593	-5.223945	2.514128	-2.08	0.038	-10.15509	-0.2928
icd_716	-3.605591	1.054699	-3.42	0.001	-5.67425	-1.536933
icd_722	-6.987658	1.454075	-4.81	0	-9.839642	-4.135674
icd_724	-3.468415	1.086933	-3.19	0.001	-5.600297	-1.336532
icd_959	-3.523162	1.510099	-2.33	0.02	-6.48503	-0.561294
_cons	39.39931	0.4821218	81.72	0	38.45369	40.34494
N	1708					
F(23, 1684)	10.1	R-squared	0.0988			
Prob > F	0	Root MSE	11.949			

Appendix C: Results

This appendix contains the full regression results for Table 3 and Table 4. A graph of the distribution of the elasticity estimates and how they differ from the long-run prediction is then provided so the reader may visibly verify that the probability distributions of the predictions are, indeed, different. It also presents the results of the initial fixed effects regressions as discussed in the text.

Appendix C Table 1: Full 3SLS Marginal Probabilities of Consuming Medical Care

Week	1		2		3		4		5		6	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	0.002	2.576**	-0.006	2.326*	-0.007	2.289*	-0.012**	2.024*	-0.015***	2.169**	-0.021***	2.209**
	(0.005)	(1.196)	(0.005)	(1.191)	(0.005)	(1.184)	(0.005)	(1.076)	(0.006)	(1.055)	(0.005)	(1.037)
Education	0.005	-0.149	0.002	-0.315	0.010***	-0.273	0.002	-0.675	0.007*	-0.614	0.004	-0.659
	(0.004)	(1.035)	(0.004)	(0.982)	(0.004)	(0.970)	(0.004)	(0.861)	(0.004)	(0.829)	(0.004)	(0.821)
Age	-0.000	3.006*	0.012*	1.835	0.012*	1.395	0.011*	1.115	0.005	1.176	0.008	1.184
	(0.007)	(1.654)	(0.007)	(1.570)	(0.007)	(1.542)	(0.007)	(1.373)	(0.007)	(1.326)	(0.006)	(1.310)
Age Squared	-0.000	-0.021	-0.000*	-0.011	-0.000*	-0.006	-0.000*	-0.006	-0.000	-0.006	-0.000	-0.006
	(0.000)	(0.014)	(0.000)	(0.013)	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.011)	(0.000)	(0.011)
Gender	-0.002	5.582	-0.036	6.059	-0.055**	6.324	-0.038	6.609	-0.063**	7.034	-0.035	5.650
	(0.027)	(6.688)	(0.028)	(6.338)	(0.026)	(6.228)	(0.027)	(5.553)	(0.027)	(5.357)	(0.026)	(5.291)
Married	0.038	10.244	0.024	8.620	0.021	10.353	-0.000	7.077	0.020	5.446	0.033	7.755
	(0.028)	(6.901)	(0.028)	(6.523)	(0.027)	(6.413)	(0.028)	(5.733)	(0.027)	(5.528)	(0.026)	(5.463)
Black	0.065	17.967	0.082	14.203	-0.064	16.212	0.009	15.358	-0.029	15.542	0.034	15.156
	(0.069)	(16.713)	(0.070)	(15.863)	(0.066)	(15.581)	(0.067)	(13.870)	(0.067)	(13.380)	(0.064)	(13.213)
White	0.120*	20.012	0.150**	17.717	0.026	18.682	0.040	15.483	0.036	15.646	0.089	14.919
	(0.064)	(15.477)	(0.065)	(14.686)	(0.061)	(14.433)	(0.063)	(12.844)	(0.062)	(12.382)	(0.059)	(12.235)
Private Ins		-26.110***		-24.174***		-22.184***		-17.676***		-17.049***		-15.773***
		(7.234)		(6.805)		(6.876)		(6.029)		(5.790)		(5.856)
Medicare		-39.613***		-41.613***		-43.165***		-34.592***		-36.185***		-37.648***
		(9.265)		(8.651)		(8.716)		(7.658)		(7.386)		(7.392)
Medicaid		-35.368***		-34.750***		-28.148***		-32.856***		-30.526***		-27.821***
		(8.967)		(8.403)		(8.533)		(7.522)		(7.273)		(7.287)
Price	-0.002**		-0.002***		-0.002**		-0.002***		-0.002***		-0.002**	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.323	-153.889**	0.241	-110.039	0.262	-105.508	0.596**	-76.766	0.826***	-86.680	0.897***	-89.941
	(0.312)	(70.309)	(0.311)	(68.053)	(0.295)	(67.351)	(0.302)	(60.400)	(0.305)	(59.093)	(0.293)	(58.130)
N	1,802	1,802	1,802	1,802	1,801	1,801	1,800	1,800	1,798	1,798	1,798	1,798

St. Error in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 1 Continued: Full 3SLS Marginal Probabilities of Consuming Medical Care

Week	7		8		9		10		11		12	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	-0.019***	2.080**	-0.017***	2.269**	-0.013**	1.969**	-0.017***	1.913**	-0.020***	1.234	-0.019***	1.455*
	(0.005)	(1.030)	(0.006)	(0.992)	(0.005)	(0.793)	(0.005)	(0.790)	(0.005)	(0.803)	(0.005)	(0.763)
Education	0.002	-0.723	0.000	-0.444	0.015***	0.255	0.011***	0.023	0.006*	0.024	0.007*	0.009
	(0.004)	(0.804)	(0.004)	(0.795)	(0.004)	(0.636)	(0.004)	(0.629)	(0.004)	(0.627)	(0.004)	(0.602)
Age	0.009	1.025	0.011*	1.108	0.008	0.660	0.010	0.720	-0.003	0.587	0.003	0.596
	(0.006)	(1.286)	(0.007)	(1.278)	(0.006)	(1.013)	(0.006)	(1.005)	(0.006)	(0.995)	(0.006)	(0.959)
Age Squared	-0.000	-0.006	-0.000	-0.006	-0.000	-0.003	-0.000	-0.004	0.000	-0.003	-0.000	-0.002
	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.009)	(0.000)	(0.008)	(0.000)	(0.008)	(0.000)	(0.008)
Gender	-0.012	5.211	-0.011	6.060	-0.016	4.890	-0.042	6.425	-0.049**	6.159	-0.048*	5.498
	(0.026)	(5.198)	(0.028)	(5.163)	(0.025)	(4.093)	(0.026)	(4.056)	(0.024)	(4.016)	(0.025)	(3.869)
Married	0.022	6.571	0.021	6.729	0.039	5.231	0.037	4.145	0.030	3.501	0.022	3.992
	(0.027)	(5.360)	(0.028)	(5.309)	(0.025)	(4.224)	(0.026)	(4.183)	(0.024)	(4.157)	(0.025)	(4.001)
Black	-0.053	14.841	-0.000	14.582	0.089	12.529	0.021	14.275	-0.036	15.044	-0.030	14.748
	(0.065)	(12.985)	(0.069)	(12.900)	(0.063)	(10.221)	(0.065)	(10.137)	(0.061)	(10.040)	(0.063)	(9.678)
White	0.022	14.276	0.092	15.657	0.170***	13.912	0.062	13.494	0.026	13.593	0.025	13.727
	(0.060)	(12.013)	(0.064)	(11.936)	(0.058)	(9.460)	(0.060)	(9.379)	(0.056)	(9.297)	(0.059)	(8.955)
Private Ins		-17.007***		-20.115***		-15.513***		-15.029***		-13.565***		-14.633***
		(5.615)		(5.415)		(4.538)		(4.354)		(4.537)		(4.251)
Medicare		-32.963***		-35.855***		-31.283***		-29.599***		-29.435***		-30.740***
		(7.175)		(6.962)		(5.725)		(5.554)		(5.709)		(5.398)
Medicaid		-32.448***		-28.231***		-24.495***		-28.155***		-27.054***		-25.324***
		(6.989)		(6.806)		(5.614)		(5.477)		(5.626)		(5.321)
Price	-0.002***		-0.003***		-0.002**		-0.003***		-0.002**		-0.003***	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.829***	-74.849	0.668**	-88.773	0.313	-75.235*	0.551*	-69.666	1.094***	-41.113	0.989***	-50.445
	(0.295)	(57.262)	(0.312)	(56.114)	(0.284)	(44.674)	(0.297)	(44.945)	(0.272)	(44.862)	(0.284)	(43.086)
N	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 2: Full 3SLS Marginal Probabilities of Consuming Medical Care for Threshold Sample

Week	1		2		3		4		5		6	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	-0.010***	2.562**	-0.010**	2.405**	-0.013***	2.314*	-0.018***	2.045*	-0.017***	2.243**	-0.019***	2.291**
	(0.004)	(1.196)	(0.005)	(1.191)	(0.005)	(1.183)	(0.004)	(1.076)	(0.005)	(1.055)	(0.004)	(1.037)
Education	0.002	-0.168	0.003	-0.111	0.007**	-0.191	-0.001	-0.647	0.004	-0.247	0.002	-0.423
	(0.003)	(1.039)	(0.004)	(0.973)	(0.003)	(0.963)	(0.003)	(0.863)	(0.003)	(0.828)	(0.003)	(0.821)
Age	-0.006	2.991*	0.008	1.914	0.008	1.409	0.011**	1.128	0.009*	1.213	0.014***	1.225
	(0.005)	(1.654)	(0.006)	(1.570)	(0.006)	(1.542)	(0.005)	(1.373)	(0.006)	(1.326)	(0.005)	(1.310)
Age Squared	0.000	-0.021	-0.000	-0.013	-0.000	-0.006	-0.000**	-0.007	-0.000*	-0.006	-0.000***	-0.006
	(0.000)	(0.014)	(0.000)	(0.013)	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.011)	(0.000)	(0.011)
Gender	0.023	5.623	0.007	5.926	-0.006	6.337	-0.024	6.537	0.004	7.232	0.001	5.657
	(0.020)	(6.689)	(0.025)	(6.336)	(0.023)	(6.227)	(0.022)	(5.553)	(0.022)	(5.357)	(0.020)	(5.291)
Married	0.031	10.196	0.030	9.384	0.035	10.709*	0.018	7.169	0.028	7.306	0.036*	8.847
	(0.020)	(6.921)	(0.026)	(6.489)	(0.023)	(6.390)	(0.022)	(5.739)	(0.022)	(5.524)	(0.021)	(5.464)
Black	0.026	18.002	0.067	14.127	0.007	16.261	0.022	15.298	-0.002	15.935	0.002	15.247
	(0.050)	(16.714)	(0.063)	(15.862)	(0.057)	(15.580)	(0.054)	(13.870)	(0.056)	(13.380)	(0.051)	(13.213)
White	0.060	19.958	0.104*	18.444	0.063	19.012	0.043	15.561	0.055	17.202	0.028	15.842
	(0.046)	(15.483)	(0.058)	(14.675)	(0.053)	(14.426)	(0.050)	(12.846)	(0.052)	(12.381)	(0.048)	(12.235)
Private Ins		-25.088***		-30.262***		-23.791***		-19.134***		-23.090***		-21.247***
		(7.497)		(6.343)		(6.552)		(6.117)		(5.731)		(5.870)
Medicare		-40.577***		-37.238***		-42.937***		-33.116***		-38.462***		-36.686***
		(9.460)		(8.250)		(8.445)		(7.731)		(7.339)		(7.402)
Medicaid		-34.507***		-37.119***		-27.771***		-34.072***		-26.765***		-27.740***
		(9.245)		(7.909)		(8.196)		(7.601)		(7.221)		(7.299)
Price	-0.001		-0.002***		-0.002***		-0.001**		-0.002***		-0.001**	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.675***	-153.841**	0.284	-113.055*	0.357	-107.505	0.604**	-76.644	0.529**	-96.083	0.524**	-95.052
	(0.225)	(70.377)	(0.279)	(67.921)	(0.255)	(67.259)	(0.241)	(60.414)	(0.254)	(59.083)	(0.235)	(58.133)
N												
Observations	1,802	1,802	1,802	1,802	1,801	1,801	1,800	1,800	1,798	1,798	1,798	1,798

St. Error in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 2 Continued: Full 3SLS Marginal Probabilities of Consuming Medical Care for Threshold Sample

Week	7		8		9		10		11		12	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	-0.014***	2.130**	-0.016***	2.277**	-0.019***	1.967**	-0.013***	1.948**	-0.017***	1.251	-0.023***	1.468*
	(0.005)	(1.029)	(0.005)	(0.991)	(0.004)	(0.793)	(0.004)	(0.790)	(0.004)	(0.803)	(0.004)	(0.763)
Education	0.002	-0.525	-0.002	-0.529	0.011***	0.184	0.006*	0.149	0.003	0.066	0.005*	0.011
	(0.003)	(0.800)	(0.003)	(0.792)	(0.003)	(0.638)	(0.003)	(0.629)	(0.003)	(0.627)	(0.003)	(0.605)
Age	0.004	1.042	0.013**	1.117	0.006	0.665	0.009*	0.718	0.006	0.596	0.002	0.611
	(0.006)	(1.285)	(0.006)	(1.278)	(0.005)	(1.013)	(0.005)	(1.005)	(0.005)	(0.995)	(0.005)	(0.959)
Age Squared	-0.000	-0.006	-0.000**	-0.007	-0.000	-0.003	-0.000*	-0.003	-0.000	-0.003	-0.000	-0.003
	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.009)	(0.000)	(0.008)	(0.000)	(0.008)	(0.000)	(0.008)
Gender	0.028	5.307	0.019	5.891	0.011	4.772	0.010	6.544	-0.033*	6.140	-0.016	5.417
	(0.023)	(5.197)	(0.024)	(5.162)	(0.019)	(4.094)	(0.022)	(4.056)	(0.020)	(4.016)	(0.019)	(3.869)
Married	0.046**	7.550	0.007	6.227	0.021	4.823	0.042*	4.814	0.051**	3.664	0.028	3.912
	(0.023)	(5.343)	(0.024)	(5.296)	(0.019)	(4.233)	(0.022)	(4.183)	(0.020)	(4.156)	(0.020)	(4.012)
Black	-0.051	15.043	-0.008	14.341	0.045	12.373	-0.042	14.405	-0.027	15.023	-0.044	14.651
	(0.057)	(12.985)	(0.060)	(12.899)	(0.048)	(10.221)	(0.054)	(10.137)	(0.050)	(10.040)	(0.049)	(9.678)
White	-0.015	15.106	0.040	15.193	0.093**	13.584	-0.013	13.977	0.016	13.730	-0.019	13.700
	(0.053)	(12.007)	(0.056)	(11.932)	(0.045)	(9.463)	(0.050)	(9.379)	(0.046)	(9.297)	(0.045)	(8.957)
Private Ins		-20.518***		-20.124***		-15.274***		-16.404***		-14.937***		-15.953***
		(5.366)		(5.221)		(4.667)		(4.354)		(4.529)		(4.416)
Medicare		-33.748***		-33.037***		-29.369***		-31.472***		-28.782***		-28.847***
		(6.987)		(6.802)		(5.825)		(5.554)		(5.702)		(5.525)
Medicaid		-30.824***		-31.208***		-26.571***		-25.927***		-27.622***		-27.172***
		(6.766)		(6.636)		(5.724)		(5.477)		(5.619)		(5.457)
Price	-0.002***		-0.003***		-0.001		-0.002***		-0.001*		-0.001*	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.659**	-79.741	0.479*	-85.642	0.516**	-72.705	0.400	-73.941*	0.602***	-41.493	0.972***	-49.297
	(0.258)	(57.216)	(0.271)	(56.081)	(0.218)	(44.695)	(0.245)	(44.945)	(0.223)	(44.860)	(0.219)	(43.114)
N	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798

St. Error in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 3: Full D3SLS Marginal Probabilities of Consuming Medical Care

Week	1		2		3		4		5		6	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	0.002	2.576**	-0.005	2.247*	-0.005	2.155*	-0.012**	1.936*	-0.010*	1.980*	-0.017***	1.971*
	(0.005)	(1.196)	(0.005)	(1.191)	(0.005)	(1.185)	(0.005)	(1.075)	(0.005)	(1.062)	(0.005)	(1.040)
Lagged Dep	0.000	-153.889**	0.187***	-9.726	0.254***	-11.584*	0.234***	-14.713***	0.251***	-8.117	0.246***	-12.420**
	(0.000)	(70.309)	(0.026)	(6.007)	(0.025)	(5.934)	(0.027)	(5.336)	(0.025)	(5.179)	(0.025)	(5.152)
Education	0.005	-0.149	0.001	-0.269	0.010***	-0.256	-0.000	-0.535	0.006*	-0.544	0.003	-0.539
	(0.004)	(1.035)	(0.004)	(0.984)	(0.004)	(0.972)	(0.004)	(0.863)	(0.004)	(0.830)	(0.004)	(0.823)
Age	-0.000	3.006*	0.013*	1.774	0.009	1.504	0.008	1.278	0.002	1.249	0.007	1.223
	(0.007)	(1.654)	(0.007)	(1.569)	(0.006)	(1.541)	(0.006)	(1.372)	(0.006)	(1.326)	(0.006)	(1.307)
Age Squared	-0.000	-0.021	-0.000*	-0.010	-0.000	-0.008	-0.000	-0.008	-0.000	-0.007	-0.000	-0.007
	(0.000)	(0.014)	(0.000)	(0.013)	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.011)	(0.000)	(0.011)
Gender	-0.002	5.582	-0.036	5.964	-0.046*	5.688	-0.026	5.582	-0.053**	6.586	-0.019	4.614
	(0.027)	(6.688)	(0.027)	(6.334)	(0.024)	(6.229)	(0.025)	(5.553)	(0.025)	(5.361)	(0.024)	(5.298)
Married	0.038	10.244	0.017	8.818	0.014	10.287	-0.004	6.980	0.022	5.520	0.027	7.891
	(0.028)	(6.901)	(0.027)	(6.528)	(0.025)	(6.418)	(0.026)	(5.728)	(0.025)	(5.531)	(0.025)	(5.462)
Black	0.065	17.967	0.071	14.563	-0.084	16.654	0.023	13.936	-0.029	15.370	0.041	14.309
	(0.069)	(16.713)	(0.067)	(15.854)	(0.062)	(15.568)	(0.064)	(13.850)	(0.063)	(13.372)	(0.060)	(13.196)
White	0.120*	20.012	0.129**	18.526	-0.011	19.831	0.034	15.334	0.027	15.874	0.080	14.997
	(0.064)	(15.477)	(0.062)	(14.687)	(0.058)	(14.436)	(0.059)	(12.819)	(0.058)	(12.376)	(0.056)	(12.217)
Private Ins		-26.110***		-23.238***		-22.324***		-17.809***		-17.718***		-16.513***
		(7.234)		(6.918)		(7.030)		(6.117)		(5.895)		(5.952)
Medicare		-39.613***		-41.448***		-40.624***		-31.831***		-35.579***		-35.587***
		(9.265)		(8.751)		(8.856)		(7.736)		(7.472)		(7.471)
Medicaid		-35.368***		-33.695***		-28.890***		-33.724***		-30.027***		-28.223***
		(8.967)		(8.524)		(8.697)		(7.605)		(7.369)		(7.374)
Price	-0.002**		-0.002***		-0.001		-0.002**		-0.002**		-0.001*	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.323	0.000	0.129	-102.380	0.188	-98.222	0.568**	-71.666	0.586**	-78.579	0.691**	-76.830
	(0.312)	(0.000)	(0.296)	(68.205)	(0.274)	(67.393)	(0.285)	(60.313)	(0.286)	(59.335)	(0.274)	(58.301)
N												
Observations	1,802	1,802	1,802	1,802	1,801	1,801	1,800	1,800	1,798	1,798	1,798	1,798
R-squared	-0.163	0.030	-0.110	0.032	0.042	0.030	-0.032	0.034	-0.015	0.033	0.043	0.036

St. Error in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 3 Continued: Full D3SLS Marginal Probabilities of Consuming Medical Care for Threshold Sample

Week	7		8		9		10		11		12	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	-0.013***	1.750*	-0.010*	1.979**	-0.009*	1.770**	-0.013**	1.726**	-0.013***	1.073	-0.010**	1.129
	(0.005)	(1.034)	(0.005)	(1.003)	(0.005)	(0.796)	(0.005)	(0.793)	(0.005)	(0.807)	(0.005)	(0.769)
Lagged Dep	0.273***	-14.843***	0.282***	-9.982*	0.297***	-9.331**	0.299***	-9.058**	0.360***	-8.062**	0.362***	-12.310***
	(0.026)	(5.107)	(0.027)	(5.216)	(0.024)	(4.049)	(0.025)	(4.091)	(0.023)	(4.067)	(0.025)	(3.919)
Education	0.000	-0.611	-0.000	-0.360	0.015***	0.227	0.007*	0.118	0.002	0.162	0.005	0.136
	(0.004)	(0.804)	(0.004)	(0.797)	(0.003)	(0.637)	(0.004)	(0.632)	(0.003)	(0.630)	(0.003)	(0.602)
Age	0.007	1.123	0.009	1.173	0.005	0.741	0.008	0.779	-0.006	0.665	0.004	0.552
	(0.006)	(1.283)	(0.006)	(1.277)	(0.006)	(1.012)	(0.006)	(1.004)	(0.005)	(0.995)	(0.006)	(0.956)
Age Squared	-0.000	-0.007	-0.000	-0.007	-0.000	-0.004	-0.000	-0.005	0.000	-0.003	-0.000	-0.002
	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.009)	(0.000)	(0.008)	(0.000)	(0.008)	(0.000)	(0.008)
Gender	-0.002	4.465	-0.008	5.871	-0.012	4.538	-0.038	6.115	-0.033	5.681	-0.031	4.775
	(0.024)	(5.192)	(0.025)	(5.159)	(0.023)	(4.089)	(0.024)	(4.052)	(0.022)	(4.019)	(0.023)	(3.865)
Married	0.014	6.978	0.016	7.064	0.033	5.041	0.025	4.166	0.018	3.908	0.010	4.536
	(0.025)	(5.354)	(0.026)	(5.313)	(0.023)	(4.225)	(0.024)	(4.185)	(0.022)	(4.159)	(0.023)	(3.997)
Black	-0.059	14.789	0.014	13.834	0.088	12.086	-0.007	14.757	-0.041	14.835	-0.016	13.923
	(0.061)	(12.955)	(0.064)	(12.893)	(0.058)	(10.207)	(0.060)	(10.126)	(0.056)	(10.030)	(0.057)	(9.655)
White	-0.000	15.226	0.086	15.808	0.141***	14.209	0.012	14.598	0.006	13.918	0.015	13.880
	(0.056)	(11.991)	(0.059)	(11.927)	(0.054)	(9.450)	(0.056)	(9.384)	(0.052)	(9.288)	(0.053)	(8.932)
Private Ins		-18.350***		-20.739***		-15.128***		-14.692***		-14.258***		-15.374***
		(5.690)		(5.546)		(4.649)		(4.441)		(4.607)		(4.313)
Medicare		-30.464***		-35.285***		-29.030***		-27.726***		-28.890***		-29.905***
		(7.226)		(7.073)		(5.824)		(5.626)		(5.764)		(5.442)
Medicaid		-33.173***		-27.184***		-25.281***		-28.933***		-26.261***		-24.606***
		(7.054)		(6.923)		(5.707)		(5.555)		(5.694)		(5.370)
Price	-0.002**		-0.002***		-0.001		-0.002***		-0.001		-0.002**	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.581**	-59.604	0.356	-77.303	0.132	-65.674	0.429	-62.662	0.879***	-36.404	0.520**	-34.203
	(0.273)	(57.388)	(0.286)	(56.453)	(0.259)	(44.768)	(0.273)	(44.983)	(0.248)	(44.913)	(0.255)	(43.309)
N												
	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798
	-0.008	0.037	-0.073	0.035	0.094	0.043	0.002	0.045	0.155	0.042	0.098	0.047

St. Error in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 4: Full D3SLS Marginal Probabilities of Consuming Medical Care for Threshold Sample

Week	1		2		3		4		5		6	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	-0.009**	2.803**	-0.007	2.390**	-0.011***	2.258*	-0.015***	1.912*	-0.011***	2.134**	-0.016***	2.154**
	(0.004)	(1.194)	(0.005)	(1.194)	(0.004)	(1.187)	(0.004)	(1.079)	(0.004)	(1.064)	(0.004)	(1.044)
Lagged Dep	0.138***	22.929***	0.283***	-0.940	0.296***	-3.151	0.277***	-10.938*	0.293***	-5.320	0.261***	-5.961
	(0.021)	(6.358)	(0.029)	(7.893)	(0.024)	(7.434)	(0.025)	(6.642)	(0.024)	(6.344)	(0.023)	(6.293)
Education	0.000	-0.361	0.003	-0.114	0.006**	-0.258	-0.003	-0.571	0.004	-0.228	0.001	-0.520
	(0.003)	(1.037)	(0.003)	(0.974)	(0.003)	(0.970)	(0.003)	(0.866)	(0.003)	(0.829)	(0.003)	(0.824)
Age	-0.007	2.862*	0.010*	1.897	0.006	1.416	0.009*	1.197	0.006	1.262	0.011**	1.265
	(0.005)	(1.648)	(0.006)	(1.571)	(0.005)	(1.542)	(0.005)	(1.373)	(0.005)	(1.327)	(0.005)	(1.310)
Age Squared	0.000	-0.019	-0.000*	-0.012	-0.000	-0.007	-0.000*	-0.007	-0.000	-0.006	-0.000**	-0.007
	(0.000)	(0.014)	(0.000)	(0.013)	(0.000)	(0.013)	(0.000)	(0.012)	(0.000)	(0.011)	(0.000)	(0.011)
Gender	0.025	6.036	0.001	5.982	-0.009	6.269	-0.024	6.345	0.013	7.057	0.001	5.488
	(0.019)	(6.666)	(0.024)	(6.338)	(0.020)	(6.228)	(0.020)	(5.551)	(0.021)	(5.361)	(0.019)	(5.290)
Married	0.027	9.847	0.022	9.417	0.026	10.355	0.009	7.300	0.024	7.457	0.026	8.316
	(0.020)	(6.898)	(0.024)	(6.497)	(0.021)	(6.414)	(0.020)	(5.747)	(0.021)	(5.530)	(0.020)	(5.472)
Black	0.026	18.123	0.061	14.180	-0.012	16.258	0.019	15.034	-0.008	15.972	0.002	14.872
	(0.049)	(16.654)	(0.059)	(15.862)	(0.050)	(15.582)	(0.050)	(13.861)	(0.052)	(13.378)	(0.048)	(13.212)
White	0.050	18.573	0.088	18.483	0.034	18.851	0.025	15.886	0.044	17.404	0.014	15.457
	(0.045)	(15.431)	(0.055)	(14.680)	(0.047)	(14.438)	(0.046)	(12.841)	(0.048)	(12.382)	(0.045)	(12.235)
Private Ins		-26.504***		-29.680***		-22.532***		-18.872***		-23.195***		-19.585***
		(7.542)		(6.419)		(6.920)		(6.286)		(5.831)		(6.007)
Medicare		-40.437***		-38.014***		-42.104***		-31.818***		-38.485***		-34.772***
		(9.437)		(8.314)		(8.751)		(7.893)		(7.421)		(7.521)
Medicaid		-34.431***		-36.402***		-28.581***		-33.758***		-26.204***		-29.540***
		(9.232)		(7.991)		(8.575)		(7.751)		(7.315)		(7.413)
Price	-0.001		-0.002***		-0.001**		-0.001		-0.001**		-0.001	
	(0.000)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.603***	-167.626**	0.095	-112.658*	0.318	-103.941	0.550**	-72.444	0.339	-92.717	0.406*	-87.469
	(0.224)	(70.252)	(0.264)	(68.199)	(0.225)	(67.417)	(0.222)	(60.457)	(0.237)	(59.266)	(0.219)	(58.318)
N												
Observations	1,802	1,802	1,802	1,802	1,801	1,801	1,800	1,800	1,798	1,798	1,798	1,798
R-squared	-0.013	0.037	-0.364	0.031	0.007	0.028	0.059	0.032	-0.025	0.032	0.066	0.033

St. Error in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix C Table 4: Full D3SLS Marginal Probabilities of Consuming Medical Care for Threshold Sample

Week	7		8		9		10		11		12	
VARIABLES	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1
Health Status	-0.009**	1.895*	-0.012***	2.177**	-0.016***	1.826**	-0.007*	1.663**	-0.012***	1.171	-0.016***	1.200
	(0.004)	(1.036)	(0.004)	(0.998)	(0.004)	(0.797)	(0.004)	(0.796)	(0.004)	(0.808)	(0.004)	(0.771)
Lagged Dep	0.303***	-11.143*	0.288***	-5.192	0.306***	-8.554*	0.288***	-12.864**	0.319***	-4.711	0.293***	-11.135**
	(0.027)	(6.358)	(0.026)	(6.329)	(0.023)	(4.911)	(0.027)	(5.116)	(0.023)	(4.943)	(0.024)	(4.812)
Education	0.002	-0.597	-0.002	-0.526	0.011***	0.194	0.003	0.286	0.002	0.093	0.004	0.039
	(0.003)	(0.801)	(0.003)	(0.796)	(0.003)	(0.638)	(0.003)	(0.631)	(0.003)	(0.629)	(0.003)	(0.605)
Age	-0.001	1.178	0.012**	1.121	0.002	0.758	0.007	0.782	0.003	0.631	0.001	0.661
	(0.005)	(1.287)	(0.005)	(1.278)	(0.004)	(1.013)	(0.005)	(1.004)	(0.005)	(0.996)	(0.005)	(0.958)
Age Squared	0.000	-0.007	-0.000**	-0.007	-0.000	-0.004	-0.000	-0.004	-0.000	-0.003	-0.000	-0.003
	(0.000)	(0.011)	(0.000)	(0.011)	(0.000)	(0.009)	(0.000)	(0.008)	(0.000)	(0.008)	(0.000)	(0.008)
Gender	0.028	5.136	0.010	5.980	0.006	4.771	0.006	6.591	-0.036*	6.123	-0.006	4.968
	(0.021)	(5.193)	(0.022)	(5.163)	(0.018)	(4.090)	(0.020)	(4.049)	(0.018)	(4.015)	(0.018)	(3.868)
Married	0.035	7.320	-0.005	6.300	0.018	4.802	0.036*	4.968	0.038**	3.810	0.014	4.379
	(0.022)	(5.346)	(0.022)	(5.313)	(0.018)	(4.233)	(0.020)	(4.179)	(0.018)	(4.162)	(0.019)	(4.015)
Black	-0.049	14.637	0.005	13.922	0.046	11.987	-0.055	14.789	-0.012	14.655	-0.035	14.081
	(0.053)	(12.975)	(0.054)	(12.907)	(0.045)	(10.215)	(0.051)	(10.120)	(0.046)	(10.046)	(0.046)	(9.667)
White	-0.022	14.707	0.044	14.891	0.080*	13.624	-0.040	14.966	0.022	13.504	-0.023	13.589
	(0.049)	(11.999)	(0.050)	(11.938)	(0.042)	(9.456)	(0.047)	(9.372)	(0.043)	(9.299)	(0.043)	(8.945)
Private Ins		-19.098***		-19.630***		-15.345***		-16.458***		-14.638***		-15.249***
		(5.449)		(5.449)		(4.723)		(4.380)		(4.607)		(4.441)
Medicare		-31.881***		-32.592***		-28.195***		-30.488***		-28.669***		-28.700***
		(7.049)		(6.999)		(5.879)		(5.570)		(5.768)		(5.541)
Medicaid		-32.223***		-30.973***		-26.223***		-26.159***		-27.160***		-26.451***
		(6.849)		(6.842)		(5.778)		(5.500)		(5.685)		(5.481)
Price	-0.002***		-0.002***		-0.000		-0.002***		-0.001		-0.001	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
Constant	0.521**	-70.635	0.295	-80.992	0.428**	-68.219	0.234	-64.886	0.458**	-39.053	0.739***	-39.631
	(0.238)	(57.313)	(0.243)	(56.356)	(0.203)	(44.738)	(0.230)	(45.005)	(0.206)	(44.950)	(0.207)	(43.248)
N												
	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798	1,798
	-0.120	0.034	-0.132	0.034	0.136	0.042	-0.054	0.046	0.124	0.040	0.110	0.045

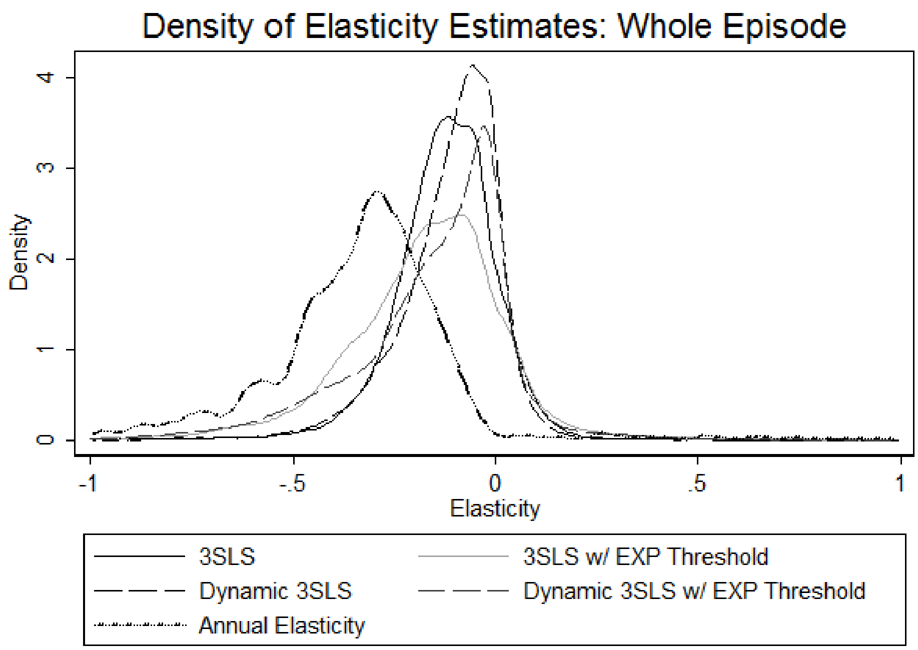

Density of Elasticity Estimates: Whole Episode
Density
0
1
2
3
4
-1
-.5
0
.5
1
Elasticity
3SLS
3SLS w/ EXP Threshold
Dynamic 3SLS
Dynamic 3SLS w/ EXP Threshold
Annual Elasticity

Table A2: Two-Stage (OLS) Marginal Probabilities of Consuming Medical Care

	No Fixed Effects				1[st] Differences Fixed Effects			
	Average Price [a]	Health Status [b]	Const.	Model Statistics	Average Price	Health Status	Const.	Model Statistics
Week 2	-0.027*** (0.005)	0.077*** (0.021)	-1.671** (0.771)	N 1803 Pr[F] 0.00	0.199 (0.189)	-0.346 (0.358)	8.249 (8.872)	N 3606 Pr[χ^2] 0.00
Week 3	-0.038*** (0.008)	0.092*** (0.026)	-2.089** (0.882)	N 1803 Pr[F] 0.00	-0.186*** (0.060)	-0.073 (0.108)	8.281* (4.865)	N 3606 Pr[χ^2] 0.00
Week 4	-0.036*** (0.007)	0.087*** (0.020)	-1.983*** (0.725)	N 1803 Pr[F] 0.00	-0.204*** (0.053)	-0.001 (0.047)	5.710** (2.355)	N 3606 Pr[χ^2] 0.00
Week 5	-0.040*** (0.008)	0.083*** (0.026)	-1.828** (0.913)	N 1803 Pr[F] 0.00	-0.589 (0.572)	0.058 (0.272)	12.679 (16.093)	N 3606 Pr[χ^2] 0.09
Week 6	-0.044*** (0.008)	0.096*** (0.024)	-2.279*** (0.865)	N 1803 Pr[F] 0.00	-0.319** (0.129)	-0.113 (0.105)	12.252** (6.152)	N 3606 Pr[χ^2] 0.00
Week 7	-0.041*** (0.006)	0.090*** (0.019)	-2.117*** (0.686)	N 1803 Pr[F] 0.00	-0.012 (0.011)	0.001 (0.010)	0.635 (0.502)	N 3606 Pr[χ^2] 0.00
Week 8	-0.050*** (0.009)	0.105*** (0.021)	-2.585*** (0.763)	N 1803 Pr[F] 0.00	-0.438*** (0.107)	-0.052 (0.079)	12.33*** (4.196)	N 3606 Pr[χ^2] 0.00
Week 9	-0.052*** (0.011)	0.122*** (0.026)	-3.140*** (0.901)	N 1803 Pr[F] 0.00	-0.699 (0.608)	0.069 (0.184)	13.470 (13.256)	N 3606 Pr[χ^2] 0.01
Week 10	-0.051*** (0.008)	0.108*** (0.020)	-2.691*** (0.729)	N 1803 Pr[F] 0.00	-1.224 (4.088)	0.075 (0.779)	24.397 (86.654)	N 3606 Pr[χ^2] 0.76
Week 11	-0.051*** (0.008)	0.095*** (0.024)	-2.237*** (0.838)	N 1803 Pr[F] 0.00	-0.445 (0.304)	-0.039 (0.110)	11.372 (8.792)	N 3606 Pr[χ^2] 0.00
Week 12	-0.053*** (0.008)	0.071** (0.035)	-1.292 (1.320)	N 1803 Pr[F] 0.00	-0.165* (0.099)	0.100* (0.060)	0.018 (0.777)	N 3606 Pr[χ^2] 0.00
Week 13	-0.053*** (0.010)	0.075* (0.041)	-1.441 (1.458)	N 1803 Pr[F] 0.00	-0.577*** (0.137)	0.007 (0.072)	12.18*** (4.045)	N 3606 Pr[χ^2] 0.00

Sample is all inpatient, outpatient, office based, and ER medical visits in Panels 8-10 (2003-2006) of MEPS for individuals experiencing an illness episode (90 days) induced by heart attack or severe (e.g. ischemic) heart condition. St. Error in parenthesis; significance levels are *** p<0.01, **p<0.05, and *p<0.1.

[a] Cumulative average out-of-pocket price is endogenous, instruments are insurance status indicators.

[b] Health status is a continuous measure on [0,100] based on ICD-9 codes for conditions diagnosed at the medical event. It is derived by predicting the continuous annual health score supplied by MEPS using all annual ICD-9 codes, and then local week-level scores were computed using these coefficients and week-level ICD-9 diagnoses.