

Essays on Medical Quality Measurement and Contract Theory

by

Daniel Lawver

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved April 2011 by the
Graduate Supervisory Committee:

Edward Prescott, Chair
Roozbeh Hosseini
Richard Rogerson

ARIZONA STATE UNIVERSITY

May 2011

ABSTRACT

This dissertation consists of three essays. The first essay studies quality increases in the medical sector. A large and growing share of income is spent on medical goods and services each year. Existing measures of the price and quantity of medical goods and services do not take changes in quality into account. Ample micro evidence suggests the quality of medical goods and services has, in fact, improved over time. This essay estimates changes in medical quality at the aggregate level. To do so, this essay develops and estimates a dynamic structural model of the demand for medical purchases. The main result of this essay is that the quality of medical goods and services has increased by 2.2 percent per year between 1996 and 2007. One implication is that, after adjusting for changes in medical quality, the relative price of medical goods and services fell by 0.5 percent per year over this period, whereas Bureau of Labor Statistics estimates suggest it rose by 1.6 percent per year.

The second essay develops a method to infer the life cycle profile of the quality of medical care in accumulating of health capital and the depreciation rate of health capital. To do so, this essay develops a life cycle model of the demand for medical purchases in which individuals invest in health capital. The use of these methods is illustrated by inferring the life cycle profile of the quality of medical care and the depreciation rate of health capital for 25-84 year old males between 1996 and 2007.

The third essay studies implementable outcomes in partnership games. In this setting, it is well known that contracts which satisfy budget balance cannot implement efficient outcomes. Then, it is natural to ask which outcomes can be implemented. This essay characterizes the outcomes of all budget balancing contracts. With standard regularity conditions on production and utility functions, all outcomes which can be implemented by a budget balancing contract can be implemented by a linear contract. This implies that, with respect to welfare, we can consider a compact

set of implementable outcomes without loss of generality. The budget-balancing contract whose outcome maximizes welfare, therefore, exists.

DEDICATION

To Wendy

ACKNOWLEDGEMENTS

I am deeply indebted to Ed Prescott, Richard Rogerson, and Roozbeh Hosseini for their advice and encouragement. I would also like to thank Hector Chade, Kevin Donovan, Berthold Herrendorf, Hubert Janicki, Jon Ketcham, David Lagakos, Claudio Lucarelli, Alejandro Manelli, Ellen McGrattan, Paul Schreck, Todd Schoellman, Jon Skinner, the seminar participants at Arizona State University, Stanford, the University of Miami, the Bureau of Economic Analysis, UC Santa Barbara, the ASHEcon conference at Cornell, the NAPW conference at Rice, and the Econometric Society Meeting in Denver for helpful discussions and comments. All remaining errors are my own.

TABLE OF CONTENTS

	Page
TABLE OF CONTENTS	v
LIST OF TABLES	vii
LIST OF FIGURES	viii
CHAPTER	1
1 MEASURING QUALITY INCREASES IN THE MEDICAL SECTOR	1
1.1 Introduction	1
1.2 Model	4
1.3 Data	10
1.4 Estimation	11
1.5 Results	15
1.6 Conclusion	26
2 ON THE ACCUMULATION AND DEPRECIATION OF HEALTH CAPITAL OVER THE LIFE CYCLE	27
2.1 Introduction	27
2.2 Basic Model	28
2.3 Inference in the Basic Model	31
2.4 Full Model	39
2.5 Data	40
2.6 Inference in the Full Model	41
Decision Rule Computation	45
2.7 Results	47
2.8 Sensitivity	49
2.9 Conclusion	54
3 A NOTE ON SHARING RULES IN TEAMS	56
3.1 Introduction	56
3.2 Model	57

Chapter	Page
3.3 Main Result	58
3.4 Welfare	62
3.5 n-Player Case	63
3.6 Conclusion	64
REFERENCES	65
APPENDIX	68
A DETAILS OF ESTIMATION PROCEDURE	68
B EXTENSION: HEALTH INVESTMENT	74
C EXTENSION: HETEROGENEITY	78

LIST OF TABLES

Table	Page
1.1 Parameter Estimates: Standard Errors in Parentheses	17
1.2 Parameter Estimates: 95.0% CI in Parentheses	25

LIST OF FIGURES

Figure	Page
1.1 Percent Decline in Mortality Rate, 1996-2007	11
1.2 Average Medical Expenditure Share of Income by Age, 1996-2007	12
1.3 Average Medical Expenditure Share of Income by Year, 25-84 Year Old Males	12
1.4 Average Co-Payment by Age Group, 1996-2007	13
1.5 Average Medical Expenditure Share of Income by Age Group, 1996-2007	15
1.6 Survival Rates by Age Group, 1996-2007	16
1.7 Lifestyle Factors $\psi_{a,t}$ by Age	18
1.8 Quality of Medical Goods and Services	18
1.9 Aggregate Medical Quality	19
1.10 Price Indexes for Medical Goods and Services	20
1.11 Real GDP	21
1.12 Counterfactual Medical Expenditure Share by Year, 25-84 Year Old Males	23
2.1 Inferred Model Parameters Relative to Baseline Estimate For Variation in x_0	34
2.2 Inferred Model Parameters Relative to Baseline Estimate For Variation in x_1	35
2.3 Inferred Model Parameters Relative to Baseline Estimate For Variation in s_0	37
2.4 Inferred Model Parameters Relative to Baseline Estimate For Variation in s_1	38
2.5 Co-Insurance Rate by Age Group	42
2.6 Survival Rate by Age Group	43
2.7 Medical Expenditures Relative to Income by Age Group	44
2.8 Life Cycle Profile of δ_a	48
2.9 Life Cycle Profile of A_a	49

Figure	Page
2.10 Inferred Medical Quality Profile For Variation in γ Relative to Average	
Medical Quality for $\gamma = 1$	51
2.11 Inferred Medical Quality Profile For Variation in η , Relative to Average	
Medical Quality for $\eta = 1$	52
2.12 Inferred Medical Quality Profile For Variation in η , Relative to Average	
Medical Quality for each η	53
2.13 Inferred Medical Quality Profile For Variation in the Value of Statistical	
Life, Relative to Average Medical Quality in the Baseline Case	54
B.1 Medical Quality, Actual and Estimated, Heterogeneity Extension	76
C.1 Medical Quality, Actual and Estimated, Health Investment Extension	80

Chapter 1

MEASURING QUALITY INCREASES IN THE MEDICAL SECTOR

1.1 Introduction

A large and growing fraction of US income is spent on medical goods and services, such as heart attack treatments and prescription drugs. Over the past fifty years, the share of income devoted to medical expenditures has more than tripled, rising from 5% to over 15%. A fundamental question is, what are Americans getting for their money? One answer is provided by the Bureau of Labor Statistics (BLS). It provides estimates of the purchase price of medical goods and services, allowing one to calculate the quantity of medical goods and services purchased by households.

A key problem with the BLS price index is that it does not take into account changes in the quality of medical purchases. Moreover, there is ample evidence that the quality of medical goods and services has increased over time. For example, Heidenreich and McClellan (2001) studies the treatment of heart attacks. Between 1975 and 1995, thirty-day mortality rates following heart attack treatment fell significantly, from 27.0% to 17.4%. Based on clinical studies, they find that most of the reduction in mortality is due to improvements in the quality of treatment over time. Many other studies find similar results for other conditions.¹ If these patterns hold in the aggregate for medical goods and services, then the BLS price index overstates the growth in the price of these goods, and correspondingly underestimates the true quantity of medical goods and services consumed.

The objective of this paper is to estimate the change in the quality of medical purchases over time at the aggregate level. The key problem is that many factors affect health outcomes. Isolating the role of medical goods and services in

¹ See, e.g., Cutler and McClellan (2001), Dugan and Evans (2005), Lucarelli and Nicholson (2009), and Shapiro, Shapiro, and Wilcox (2001)

determining health outcomes is difficult, making it difficult to measure medical quality. To illustrate this problem, consider a simple example. Suppose individuals in 1996 each take one “year 1996” pill, and 90 percent of these individuals survive to 1997. Individuals in 2007 each take one “year 2007” pill, and 95 percent of these individuals survive to 2008. Why did survival rates change over time? Without more information, there is a continuum of possibilities. On one hand, changes in pill quality may be responsible for all of the observed change in survival rates. On the other hand, pill quality may not have changed at all, and changes in other factors are responsible for the change in survival. People in 2007 may smoke at lower rates, eat less red meat, exercise more, breathe higher quality air, or work at less stressful jobs. As a result, information on survival rates and medical utilization is not enough to infer medical quality. In order to measure the quality of medical goods and services, one must carefully correct for the role of non-medical factors – such as the lifestyle and environmental factors listed previously – in determining survival.

One way to solve this problem is to consider the demand for medical goods and services. The parameters which affect survival rates – non-medical factors and medical quality – also affect the demand for medical purchases. In particular, the marginal value of medical purchases depends on the quality of medical purchases and on non-medical factors. Non-medical factors determine the potential for medical purchases to improve health outcomes, and medical quality affects the rate at which medical purchases improve health outcomes. The more individuals have to gain by seeking treatment, either because medical quality is high or non-medical factors are poor, the higher the marginal value of medical purchases. As a result, medical decisions reveal information about the ability of medical goods and services to improve health outcomes. Utilizing a model in which health outcomes and medical purchases are endogenous, the quality of

medical goods and non-medical factors can be inferred using observations of medical purchases and health outcomes.

This paper implements this solution in order to estimate changes in the quality of medical goods and services at the aggregate level. To do so, I develop a dynamic structural model of demand for medical goods and services. This model has three key features: medical purchases are endogenous, survival rates are endogenous, and non-medical factors affect survival rates. I estimate this model using data on medical purchases and survival rates for males in the US between 1996 and 2007. My estimates suggest that medical quality has increased rapidly over this period, by about 2.2% per year. This implies that the relative price of medical goods and services, after adjusting for quality change over time, has actually fallen by about 0.5% per year. This is in sharp contrast to BLS estimates in which the relative price of medical goods and services has risen by 1.6% per year over this period. Another implication is that growth in real GDP is underestimated. Measures in the national accounts suggest that real GDP has grown by 3.1% per year over this period. My estimates, which take into account changes in medical quality, suggest that real GDP has grown by 3.4% per year over this period.

This paper is related to several others in the literature which study changes in the quality of medical goods and services over time. Lichtenberg and Virabhak (2007) finds that newer drugs are more productive than older drugs, in the sense that newer drugs produce better health outcomes. If older drugs are being replaced by newer drugs over time, the quality of prescription drugs is increasing over time at the aggregate level. This paper estimates medical quality at the aggregate level rather than among a subset of medical goods. Cutler and McClellan (2001) surveys five condition-level studies of changes in the costs and benefits of new medical treatments. They find that improvements in health outcomes generally exceed increases in treatment costs. They conjecture that,

properly measured, the relative price² of medical goods and services is actually declining over time at the aggregate level. This paper evaluates that conjecture.

This paper is also related to another group of papers which study aggregate medical expenditures in the US. Hall and Jones (2007) argues that it is reasonable to believe that the current share of income devoted to medical expenditures is optimal, and that it is also reasonable to believe it will be optimal to spend an even higher share of income on medical goods in the future. Suen (2006) studies the rise in medical expenditures and life expectancy in the US since 1950, and argues that all of the rise in medical expenditures and sixty percent of the rise in life expectancy can be explained by increases in income and improvements in medical technology. In order to address these questions, both papers make assumptions about the growth rate of medical quality at the aggregate level. I complement these papers by developing methods to estimate the quality of medical goods. Better estimates of medical quality will allow for improved answers to these questions.

The paper is organized as follows. In Section 2, the model is presented and various modeling assumptions are discussed. In Section 3, the data is described. In Section 4, the estimation procedure is outlined. Section 5 presents results, and Section 6 concludes.

1.2 Model

In this section, I develop a dynamic model of demand for medical goods similar to the model in Hall and Jones (2007). The economy is populated by cohorts of finitely-lived individuals. Each individual is endowed with a lifetime stream of income. Agents value medical consumption and non-medical consumption. Individuals value medical consumption because of the associated increases in

² This study uses relative price to mean the price relative to the Consumer Price Index (CPI). I avoid this usage of relative price because medical prices are a component of the CPI, but are not a component of the non-medical consumption price index.

period utility and the probability of surviving to the next period. Survival rates also depend on exogenous non-medical factors. I discuss various modeling assumptions after specifying the model.

Demographics

Time is discrete, and starts at year $t=0$. Each year, a new cohort of individuals is born at age 1. Individuals are indexed by their age a and the time period t in which they make decisions. Individuals in each (a, t) group are identical, i.e. I abstract from within-cohort heterogeneity. The mass of individuals of age a in period t is $\omega_{a,t}$. In each period, agents allocate income to purchases of medical goods, non-medical consumption, and assets. A fraction $s_{a,t}$ survive to the next period. Individuals live a maximum of T years.

Medical Quality

Individuals value medical goods and services $x_{a,t}$ for two reasons. First, they value the associated increases in the current period's survival rate, and second, they value to associated increases in the current period's utility flow. Quality $A_{a,t}$ is a measure of the degree to which medical goods increase the survival rate and utility flow for individuals of age a in period t . One can think of $x_{a,t}$ as the number of pills that an individual purchases, and $A_{a,t}$ as the quality of each pill. This quality measure is defined so that the product of the quality and quantity of medical goods is the measure of their ability to improve health outcomes. Quality, quantity pairs (A_1, x_1) and (A_2, x_2) , then, are valued equally by individuals if $A_1x_1 = A_2x_2$. With this in mind, I define medical consumption to be the product of the quality and quantity of medical purchases.

Preferences

Individuals order life cycle profiles³ of medical consumption, non-medical consumption and survival rates $\{A_a x_a, c_a, s_a\}_{a=1}^T$ according to

$$\sum_{a=1}^T \left\{ \prod_{i=1}^{a-1} s_i \right\} \beta^a u(c_a, A_a x_a) \quad (2.1)$$

where $\left\{ \prod_{i=1}^{a-1} s_i \right\}$ is the probability that an individual lives to age a , and $\beta > 0$ is the discount factor. The utility of death is normalized to zero.

The period utility function u is written as:

$$u(c_{a,t}, A_{a,t} x_{a,t}) = \alpha \log(c_{a,t}) + (1 - \alpha) \log(A_{a,t} x_{a,t}) + \phi \quad (2.2)$$

where $0 \leq \alpha \leq 1$ is the weight that individuals place on non-medical consumption and ϕ is a constant.⁴

Survival Function

An individual's survival rate $s_{a,t} = g(A_{a,t} x_{a,t}, \psi_{a,t})$ depends on non-medical factors $\psi_{a,t}$, the quantity of medical goods, and the quality of medical goods. The function g is written as:

$$g(A_{a,t} x_{a,t}, \psi_{a,t}) = \psi_{a,t} + (1 - \psi_{a,t}) \frac{A_{a,t} x_{a,t}}{A_{a,t} x_{a,t} + 1} \quad (2.3)$$

where $\psi_{a,t} \in [0, 1]$ denotes the role of non-medical factors in the survival function.

The function g is twice continuously differentiable, increasing, strictly concave, and takes values in $[0, 1)$. The 1 in the denominator in the second term on the

³ To avoid cumbersome notation, life cycle profiles are not indexed by time here

⁴ This term is commonly used in environments with endogenous survival rates (see, e.g., Hall and Jones (2007), Becker et al (2005)). This term is important because the level of period utility matters in models with endogenous survival rates. In particular, if period utility is lower than the value of death in each period, then individuals do not value decreases in mortality.

right-hand side is a scaling parameter, and can be normalized to one without loss of generality.⁵

Budget

An individual's period budget constraint is written as:

$$c_{a,t} + \theta_{a,t} p_t^x x_{a,t} + k_{a+1,t+1} \leq y_{a,t} + Rk_{a,t} \quad (2.4)$$

where $\theta_{a,t}$ is the share of medical expenses paid by the individual, p_t^x is the purchase price of medical goods and services relative to non-medical consumption, $x_{a,t}$ is purchases of medical goods, $k_{a,t}$ is asset, R is the net return on assets, and $y_{a,t}$ is income net of transfers. The price of non-medical consumption is normalized to be one in each period. Assets are constrained to be non-negative in all periods. Income net of transfers $y_{a,t}$ is written as

$$y_{a,t} = w_{a,t} + B_t - P_{a,t} \quad (2.5)$$

where $w_{a,t}$ denotes the period endowment, $P_{a,t}$ denotes health insurance premiums paid by individuals, and B_t denotes accidental bequests. Accidental bequests are redistributed evenly in each period, and are written as:

$$B_{t+1} = \sum_{a=1}^T (1 - s_{a,t}) k_{a+1,t+1} \quad (2.6)$$

Decision Problem

In each period, individuals choose non-medical consumption, purchases of medical goods and services, and the amount of assets to carry forward to the next

⁵ Notice that, if this term is doubled, all $A_{a,t}$ are doubled, and $x_{a,t}$ remains fixed, $s_{a,t}$ does not change. This term scales the estimates of $A_{a,t}$

period, contingent on survival. This decision problem is written as follows:

$$v_{a,t}(k_{a,t}) = \underset{x_{a,t}, c_{a,t}, k_{a+1,t+1}}{Max} [u(c_{a,t}, A_{a,t}x_{a,t}) + \beta s_{a,t}v_{a+1,t+1}(k_{a+1,t+1})] \quad (2.7)$$

$$\text{subject to: } c_{a,t} + \theta_{a,t} p_t^x x_{a,t} + k_{a+1,t+1} \leq y_{a,t} + Rk_{a,t}$$

$$s_{a,t} = g(A_{a,t}x_{a,t}, \psi_{a,t})$$

$$k_{a+1,t+1} \geq 0$$

Decomposing Medical and Non-Medical Factors

The goal of this exercise is to estimate medical quality. To do this, the roles of medical and non-medical factors in determining survival rates must be decomposed. In other words, $A_{a,t}$ and $\psi_{a,t}$ must be disentangled using observations of medical spending decisions $x_{a,t}$ and realized survival rates $s_{a,t}$ in the data. Recall the survival function in equation (2.3). Given observations of medical purchases and survival rates and this functional form, there is a curve of pairs $(\psi_{a,t}, A_{a,t})$ such that survival rates in the model match the data. As mentioned previously, without considering more information, it could be that medical purchases increased survival rates from 0 to $s_{a,t}$, or that medical purchases had no effect at all on survival. Mathematically, the problem is that the two unknowns cannot be disentangled using a single equation.

In order to disentangle the two unknowns, the demand for medical goods and services is taken into consideration. Mathematically, this means that two equations are used to disentangle the two unknowns. The intuition behind this approach is that the demand for medical purchases, derived from equation (2.7), is increasing in $A_{a,t}$ ⁶, and decreasing in $\psi_{a,t}$. The demand for medical purchases will rise if they become more effective at reducing mortality, and decrease if an individual's initial survival rate increases. Survival rates are increasing in each

⁶ This is true for values of $A_{a,t}$ that are reasonably low. Estimates of $A_{a,t}$ fall within this range

variable $A_{a,t}$ and $\psi_{a,t}$. Fixing all other factors, this implies that, for each age, time observation, there is a unique pair $(\psi_{a,t}, A_{a,t})$ such that model predictions for the corresponding individual's survival rate and demand for medical purchases matches the data.

Discussion

The period utility function u depends on medical consumption. This feature of the model captures the fact that medical expenditures are important for current well-being as well as longevity. The parameter α is the weight that individuals place on utility from medical consumption. Quality growth is assumed to be the same for both uses of medical goods and services: survival and contemporaneous utility. This assumption is made for practical reasons, since the utility flow from medical expenditures is not observable. I explore the implications of this assumption in Section 5.

One feature of the budget constraint is that individuals pay for a fraction of medical expenses out of pocket. This is an important assumption because, on average, individuals pay for a small portion of their medical expenses directly. Most expenses are paid indirectly through public or private insurance. The marginal cost of one dollar of medical expenses for individuals, then, is generally much lower than one dollar. I want to emphasize that this is a coarse approximation of the institutional details that determine the marginal cost of medical purchases for individuals. In reality, individuals with different types of health insurance face different co-payment schedules for different types of treatment. This simplification provides an approximation of the average marginal cost that these individuals face.

In this model, medical expenditures affect this period's survival rate, but not an agent's survival rate in the next period – $\psi_{a+1,t+1}$ – contingent on surviving to the next period. To a certain degree, medical expenditures are an investment in

future health.⁷ I explore the implications of this assumption in greater detail in the appendix. Another simplifying assumption is that there is no heterogeneity within cohorts. In reality, there are big differences in medical expenditures within cohorts. Presumably, this is due to heterogeneity with respect to non-medical factors within these cohorts. One concern is that abstracting from within-cohort heterogeneity may lead to incorrect estimates of the medical quality. I explore this assumption in greater depth in the appendix.

1.3 Data

In this section, I describe the data that is used to estimate the model, and document facts related to medical expenditures and survival rates in the US for 25-84 year old males over the period 1996-2007. The data used here are annual and come from the Medical Expenditure Panel Survey (MEPS) and the Social Security Administration (SSA). The MEPS also reports data on income and medical expenditures at the individual level. I use this individual-level data to construct age-level data in each period by averaging across individuals in that age, time group. The MEPS reports medical payments by source. To calculate the average co-payment rate that individuals pay, I calculate the share of total medical expenses that are paid by each group. Out-of-pocket payments make up a small fraction of medical expenses, and there is considerable variation in the out-of-pocket share across age, time groups. The share of medical expenses paid out of pocket generally declines with age and time. This pattern is shown in Figure 2.5. The MEPS also reports the share of single-person health insurance premiums that are paid by employers and employees, which is used to calculate the health insurance premiums paid by employees.

The SSA reports mortality rates, realized and projected, at every age for every ten-year period between 1990 and 2100. I construct mortality rates in years

⁷ For a theoretical treatment of this topic, see Grossman (1972)

that are not reported using linear interpolation. Figure 1 shows the change in mortality rates by age between 1996 and 2007. This figure shows that mortality rates declined over this period. Among all groups, mortality declined by an average of twelve percent.

Figure 1.1: Percent Decline in Mortality Rate, 1996-2007

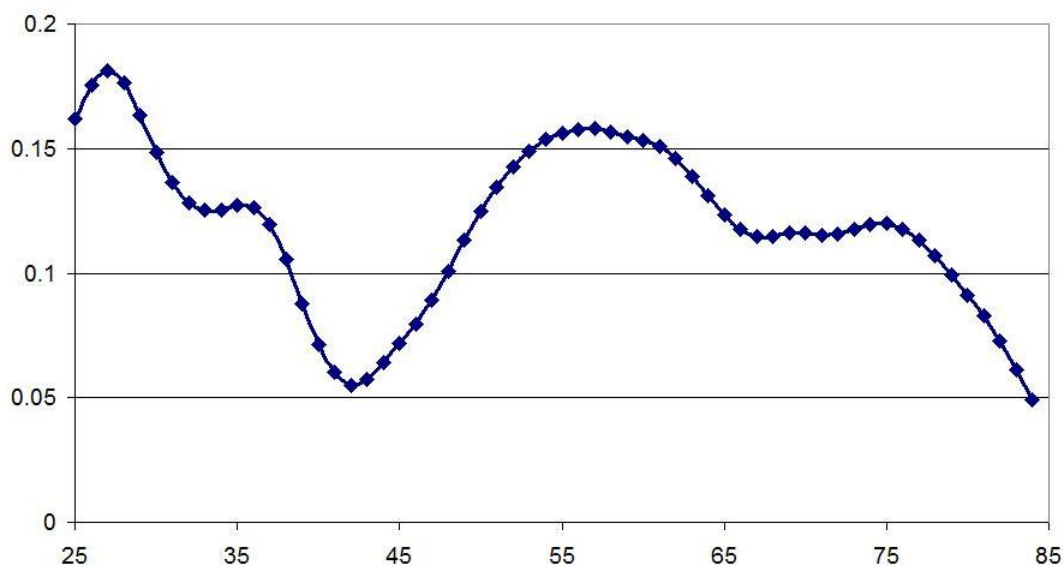


Figure 2 shows medical expenditures relative to income by age averaged over 1996 to 2007. The share of income devoted to medical expenditures rises quite sharply with age.

Figure 3 shows medical expenditures relative to income among 25-84 year old males between 1996 and 2007. The share of income devoted to medical expenditures rises, on average, over the time period.

1.4 Estimation

In this section, I outline the estimation procedure. Model parameters are chosen as follows. The parameter β is chosen to be .96, and the return on savings R is chosen to be $1/\beta$. Some model parameters are chosen directly by matching their observed empirical counterparts. These parameters determine income $(w_{a,t})$,

Figure 1.2: Average Medical Expenditure Share of Income by Age, 1996-2007

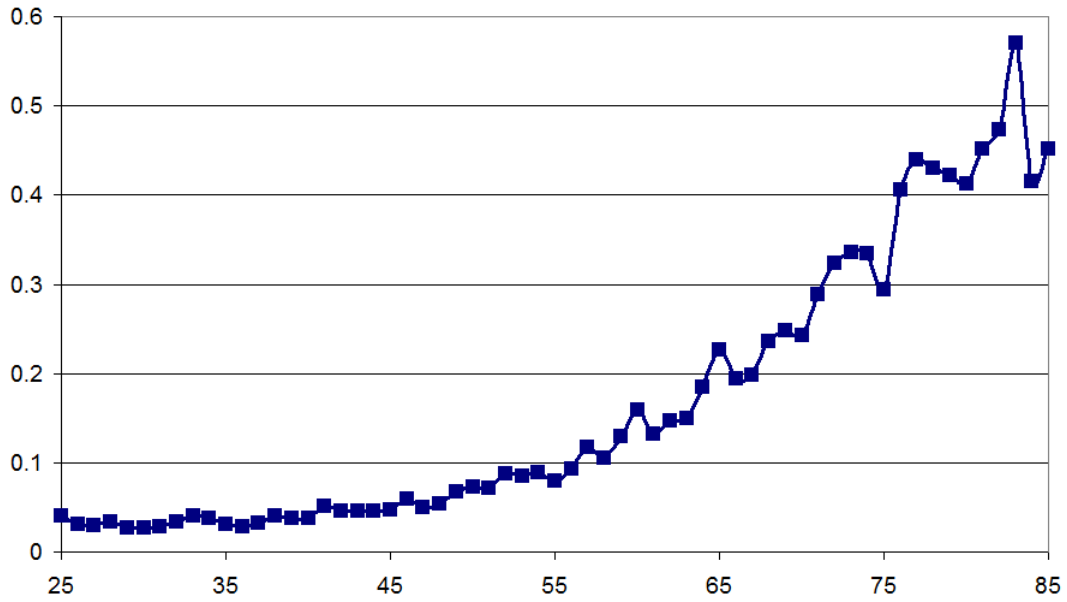


Figure 1.3: Average Medical Expenditure Share of Income by Year, 25-84 Year Old Males

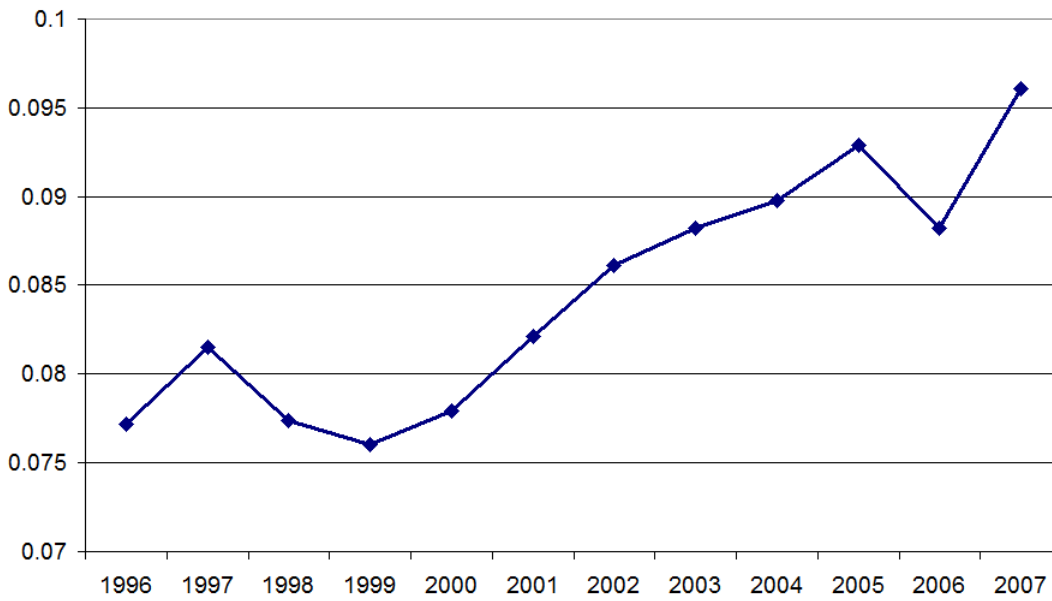
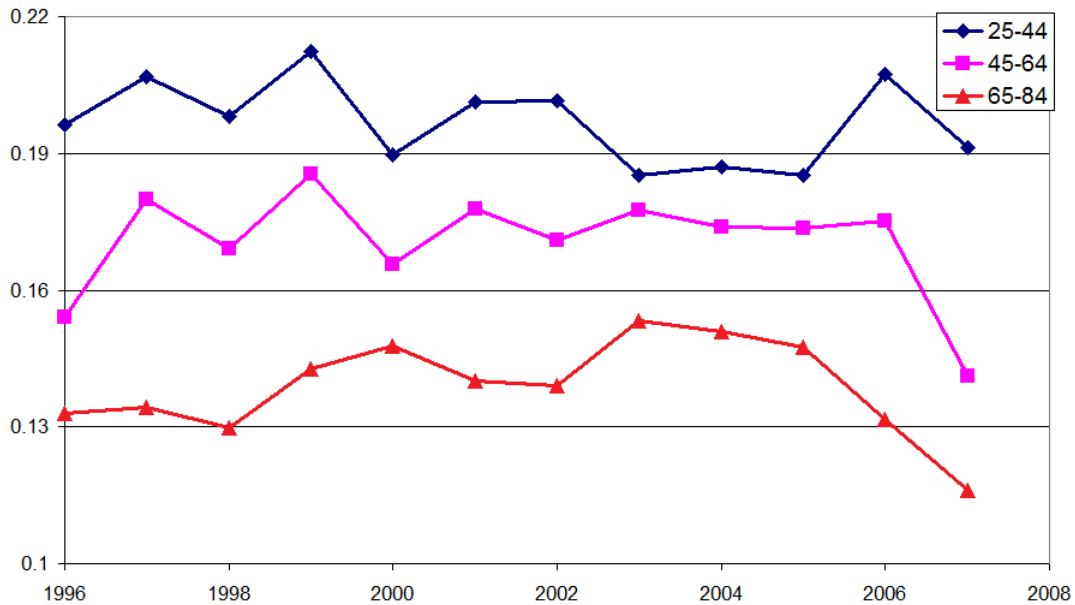


Figure 1.4: Average Co-Payment by Age Group, 1996-2007



purchase prices (p_t^x), premiums ($P_{a,t}$), and co-payment rates ($\theta_{a,t}$).⁸ Future values of these parameters with empirical counterparts are projected based on available observations. In particular, income, prices, and premiums are projected forward assuming that they have a linear time trend. Co-payment rates are held fixed at their 2007 values. Individuals older than 85 are not included in the MEPS. I assume that individuals 85 and older have income, premiums, and co-payment rates are equal to those of 84 year-olds. Time zero in the model corresponds to 1996, the first year for which MEPS data is available. Age 1 in the model corresponds to 25 years old, and decisions are made over $T = 75$ periods. All agents die with probability one at age 100.

The constant term in flow utility ϕ is chosen so that the value of a statistical life for 35-44 year-olds in 2000 in the model is 9.9 million dollars,⁹ matching the

⁸ Note that this is a measure of the average co-payment rate, as opposed to the marginal co-payment rate.

⁹ This procedure is also used by Hall and Jones (2007) to choose the constant term in the period utility function.

estimate in Aldy and Viscusi (2008).¹⁰ The value of a statistical life is the present value of an individual's expected consumption stream over the remainder of their life. Following Kniesner, Viscusi, and Ziliak (2006), the average value of a statistical life for 35-44 year-old males in 2000, which I will call VSL , is calculated as follows:

$$VSL = \frac{1}{10} \sum_{a=35:44} \frac{1}{u'(c_{a,2000})} v_{a,2000}(k_{a,2000})$$

where, for convenience, the indexes correspond to the actual age and year as opposed to the age and year indexes. Recall, also, that v is the value function in equation (2.7).

I restrict the set of medical quality parameters. In each year, medical quality is the same within three age groups: 25-64 year-olds, 65-74 year-olds, and 75-99 year-olds.¹¹ Medical quality will be the same, for example, for all individuals aged 25-64 in each year. These time series are called $A_{25-64,t}$, $A_{65-74,t}$, and $A_{75-99,t}$. These groups are chosen because I want as few groups as possible subject to matching the data well. Model predictions for medical spending improve dramatically if quality is estimated for three groups rather than one or two. Adding more groups results in a minor reduction in the difference between model estimates and data. I estimate these quality parameters for each year between 1996 and 2007. After 2007, medical quality grows at a constant rate $\gamma_{i,A}$ equal to the average growth rate for group i between 1996 and 2007.

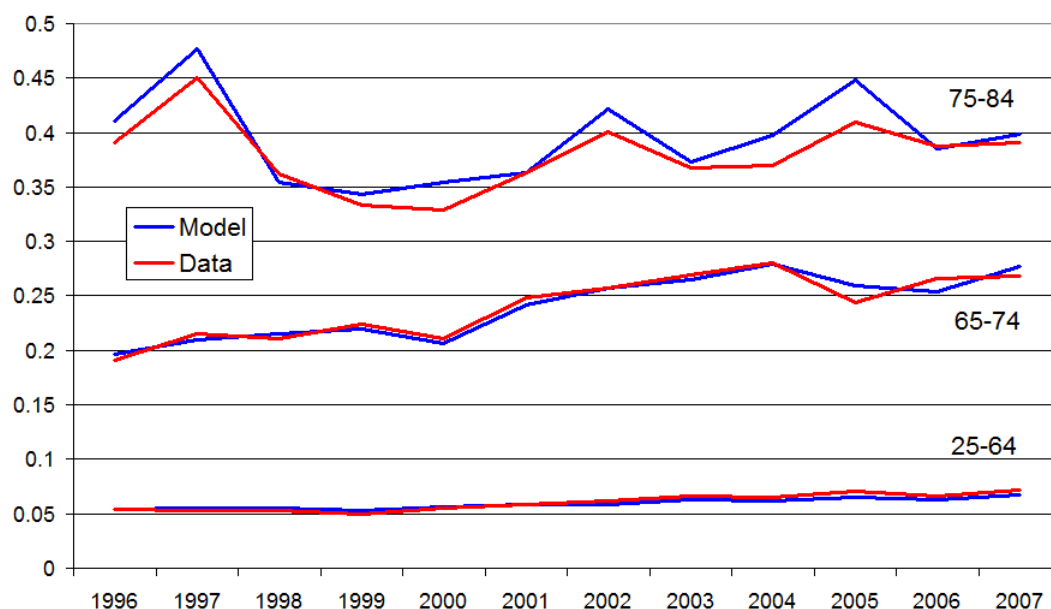
The basic strategy is to choose the remaining parameter values so that model predictions for medical expenditures and survival rates closely match the data. The main problem lies in the fact that there are a very large number of $\psi_{a,t}$

¹⁰ There is considerable variation in estimates of the value of a statistical life. For a survey, see Viscusi and Aldy (2003). I will explore the sensitivity of this choice of the value of a statistical life in Section 5.

¹¹ Note that the third group effectively consists of 75-84 year-olds, as data for individuals over 84 isn't used to estimate the parameter

parameters to estimate. This problem is solved by converting the estimation procedure into a fixed point problem. This procedure is detailed in the appendix. This procedure is very effective at choosing a parameter vector for which model decision rules and survival rates closely match the data. I demonstrate the fit in figures 5 and 6. In figure 5, I plot the time series for average medical expenditure shares for 25-64, 65-74, and 75-84 year-olds between 1996 and 2007 in the estimated model and in the data. In figure 6, I plot the time series for average survival rates for 25-64, 65-74, and 75-84 year-olds between 1996 and 2007 in the estimated model and in the data. The value of a statistical life for 35-44 year-olds in 2000 in the model is equal to 9.9 million dollars, matching the previously mentioned target.

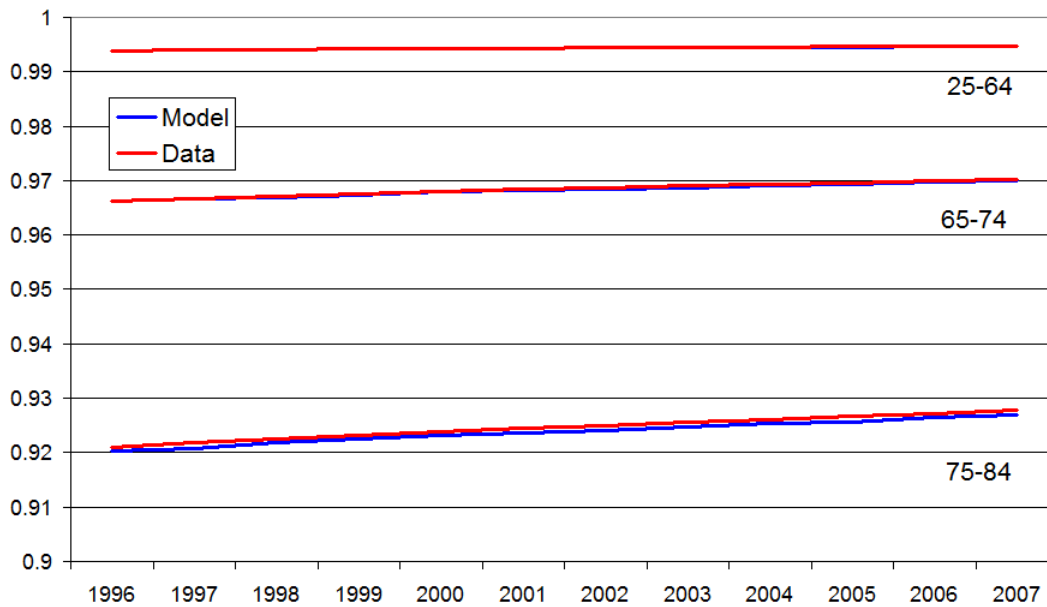
Figure 1.5: Average Medical Expenditure Share of Income by Age Group, 1996-2007



1.5 Results

This section presents the results of the estimation. Non-medical factors $\psi_{a,t}$ for each age group in 1996 and 2007 are reported graphically in Figure 1.7.

Figure 1.6: Survival Rates by Age Group, 1996-2007



Non-medical factors have improved among all groups over this period. The largest improvements are among the elderly.

Parameter estimates for preference parameters and medical quality are reported in Table 1.1. One important observation is that the parameter α is very close to one, meaning that individuals put a small weight on utility from medical consumption. The parameter ϕ is calibrated as discussed in the previous section, and no standard error is computed.

Quality growth for each age group is plotted for each year between 1996 and 2007 in Figure 1.8. Since I am interested in quality change over time, I normalize medical quality for each group to be one in 1996 in the figure.¹² Quality has increased among all three groups. Medical quality is growing at about the same rate among the two elderly groups, and faster among the youngest group.

¹² There are level differences among the groups. As you'll notice in Table 1, medical quality is higher among younger groups. This is likely due to the decline in the immune system associated with aging (see Holliday (1995)), among other factors.

Table 1.1: Parameter Estimates: Standard Errors in Parentheses

Preference Parameters			
α	.993 (4.21e-4)		
ϕ	9.68		
Medical Quality Parameters	Ages 25-64	Ages 65-74	Ages 75-99
1996	1.36e-5 (0.98e-6)	1.17e-5 (0.36e-6)	1.00e-5 (0.13e-6)
1997	1.42e-5 (0.97e-6)	1.21e-5 (0.33e-6)	1.06e-5 (0.11e-6)
1998	1.43e-5 (1.07e-6)	1.24e-5 (0.35e-6)	1.01e-5 (0.15e-6)
1999	1.40e-5 (1.36e-6)	1.25e-5 (0.32e-6)	1.02e-5 (0.17e-6)
2000	1.52e-5 (1.17e-6)	1.25e-5 (0.28e-6)	1.05e-5 (0.16e-6)
2001	1.59e-5 (1.07e-6)	1.32e-5 (0.29e-6)	1.07e-5 (0.16e-6)
2002	1.61e-5 (1.09e-6)	1.35e-5 (0.27e-6)	1.13e-5 (0.12e-6)
2003	1.77e-5 (0.78e-6)	1.36e-5 (0.28e-6)	1.11e-5 (0.14e-6)
2004	1.75e-5 (0.87e-6)	1.40e-5 (0.25e-6)	1.14e-5 (0.13e-6)
2005	1.86e-5 (0.85e-6)	1.37e-5 (0.30e-6)	1.20e-5 (0.12e-6)
2006	1.83e-5 (1.15e-6)	1.37e-5 (0.30e-6)	1.17e-5 (0.15e-6)
2007	1.91e-5 (0.92e-6)	1.43e-5 (0.26e-6)	1.20e-5 (0.18e-6)

This result is likely driven by the relative growth rate of medical expenditures across groups. Expenditures grew faster among the non-elderly than the elderly,¹³ which implies that the marginal value of medical expenditures grew faster among the young.

Aggregate Medical Quality

I construct an estimate of aggregate medical quality A_t using estimates of group-specific medical quality in each period. To do so, I compute the expenditure-weighted average of medical quality among the three groups. The time series for aggregate medical quality is presented in Figure 9. My estimates imply that medical quality rose by 25 percent over this period.

I use the time series for medical quality to compute the relative quality-adjusted price of medical goods and services p_t^{QA} using the relative price

¹³ This pattern is also noted in Meara, White, and Cutler (2004)

Figure 1.7: Lifestyle Factors $\psi_{a,t}$ by Age

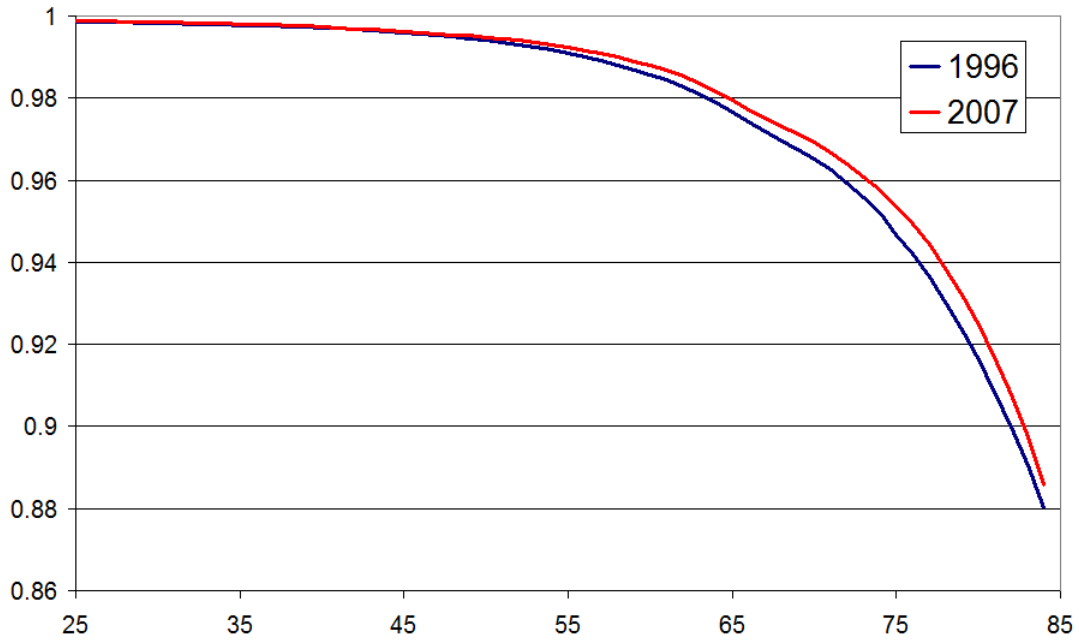


Figure 1.8: Quality of Medical Goods and Services

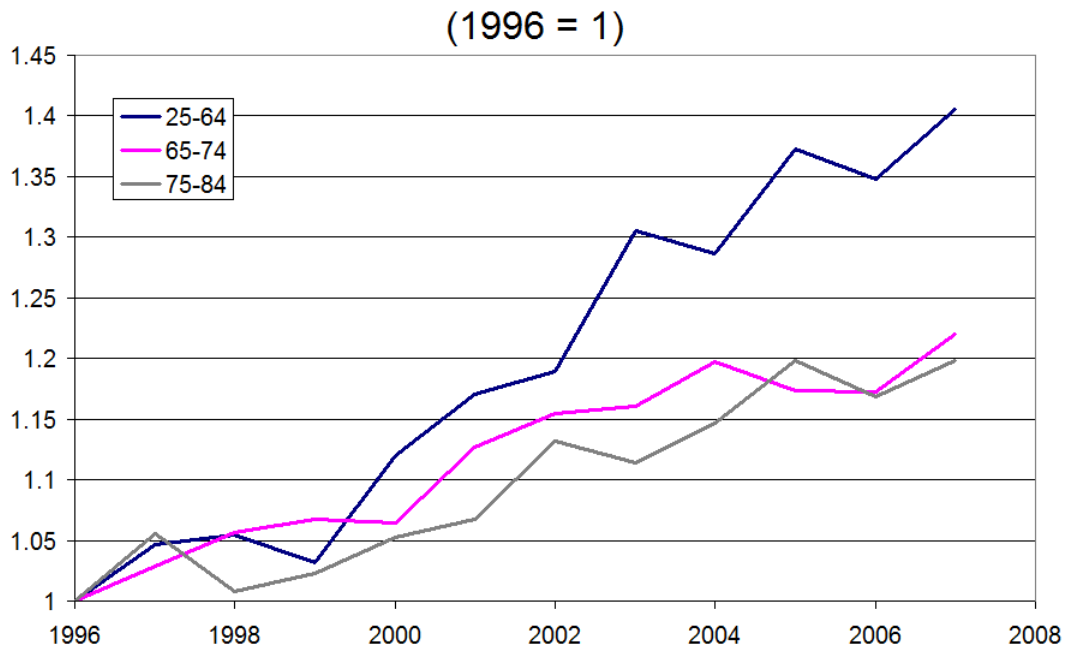
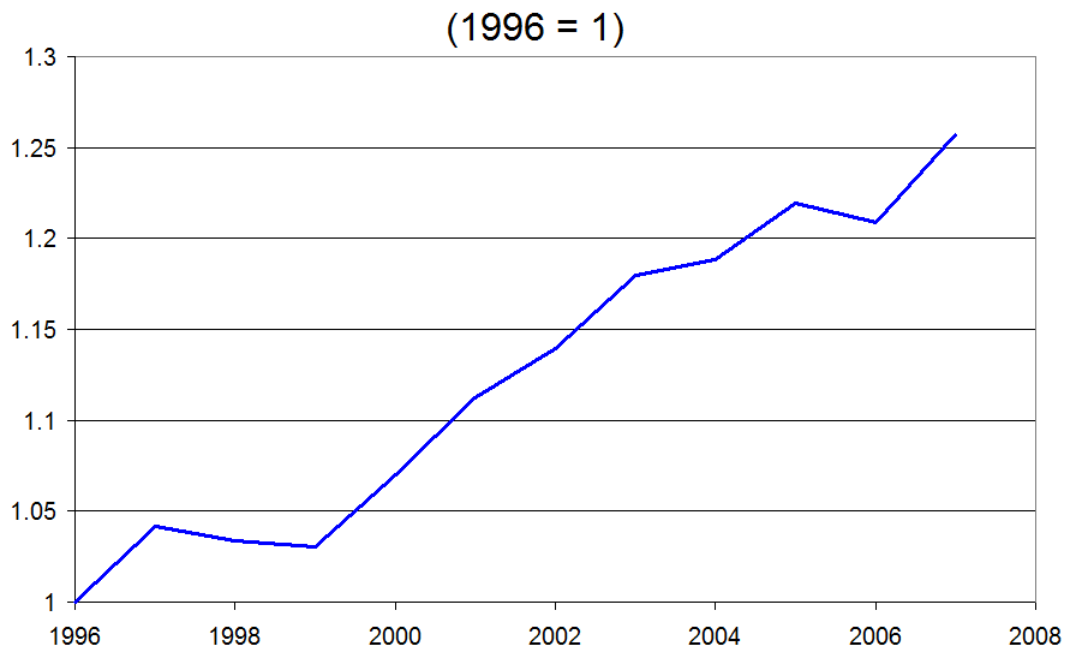


Figure 1.9: Aggregate Medical Quality



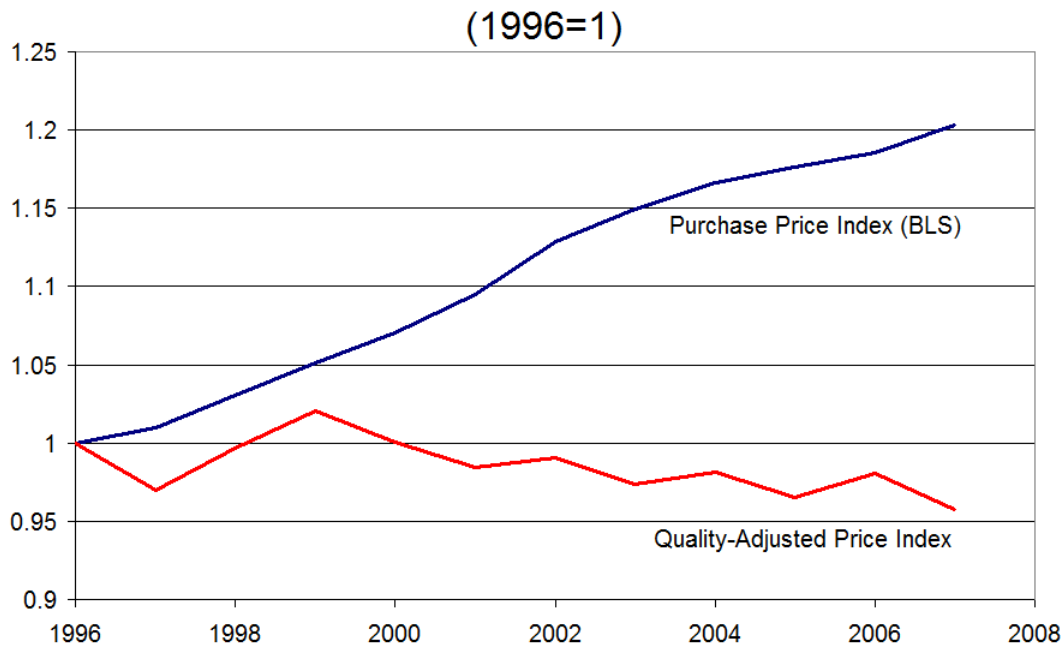
index constructed by the BLS p_t^{BLS} and quality A_t of medical purchases as follows:

$$p_t^{QA} = \frac{p_t^{BLS}}{A_t}$$

The time series for both relative price indexes are reported in Figure 10. Based on BLS estimates, the relative price of medical goods increased by twenty percent over this period. My estimates suggest that, after taking changes in the quality of medical purchases into account, the relative price of medical goods and services fell by five percent over this period.

Recall that measures of the output of the medical sector in the national accounts do not take changes in the quality of medical purchases into account. The use of this accounting convention is inconsistent with my findings that the quality of medical purchases has increased over time, implying that real medical output is under-measured in the national accounts. This, in turn, implies that real output is under-measured in the national accounts. I measure the extent to which real GDP growth is under-measured do to mis-measurement of the output of the

Figure 1.10: Price Indexes for Medical Goods and Services

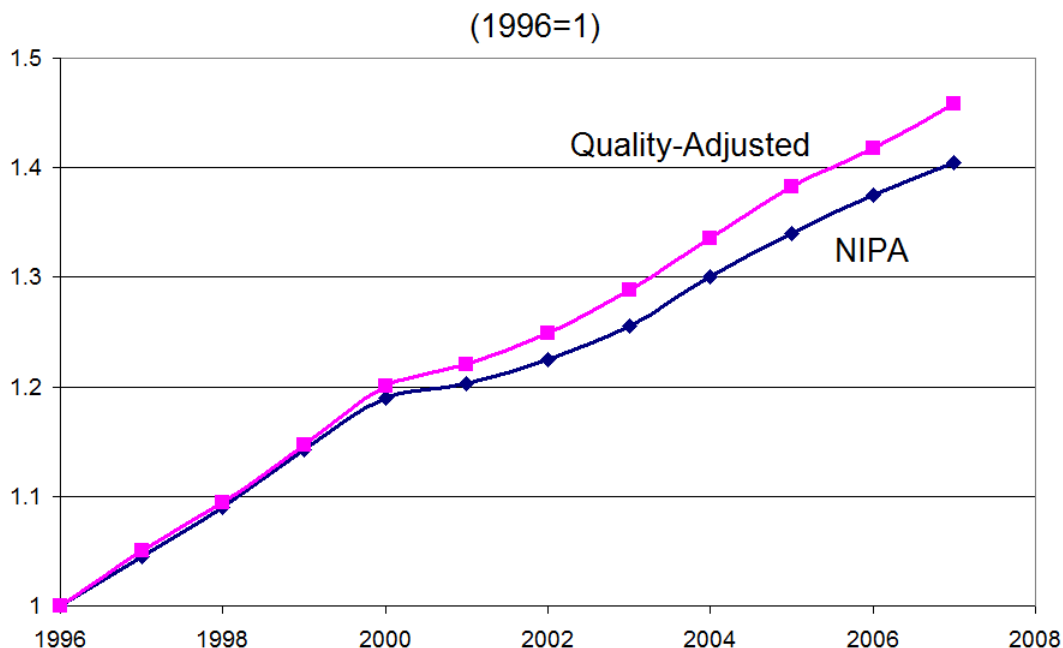


medical sector. To do so, I use data from the National Health Expenditure Accounts for estimates of the size of the medical sector. I use estimates from the National Income and Product Accounts for real GDP. To calculate my revised estimates of GDP, I assume that quality growth in the medical sector is the same as my estimates suggest. This is an important caveat because I used only a subset of the population to make my estimates. My estimates suggest that, between 1996 and 2007, real GDP grew at 3.4% per year, while reported real GDP grew at 3.1% per year. These estimates of real GDP are reported in Figure 1.11.

Sensitivity

My main finding is that the quality of medical goods and services has increased quite rapidly between 1996 and 2007. In this section, I perform sensitivity analysis to see if this result depends critically on various assumptions regarding specific parameter values or projections for future variables. I estimate the model for alternative values of β and using alternative projections for income and survival

Figure 1.11: Real GDP



rates. For both survival rates and income, I estimate the model in the case that their growth rate after 2007 is five percent higher or lower than baseline projections. I also explore the implications of assumptions regarding utility from medical consumption. I estimate the model in the case that $\alpha = 1$, meaning that individuals get no utility from medical consumption. I also estimate the model in the case that the quality of medical goods and services in increasing the utility flow is constant over time. Recall that I choose ϕ so the value of a statistical life for 35-39 year-olds in 2000 is 9.9 million dollars. I do the same exercises in the cases that this value is two million dollars and four million dollars. Over all of these alternative specifications mentioned here, medical quality growth varied within one percentage point of the baseline estimate of 25 percent.

I also explore the implications of various modeling assumptions on the estimation of medical quality. To do this, I generate synthetic data using extended versions of the model to explore the extent to which various modeling assumptions

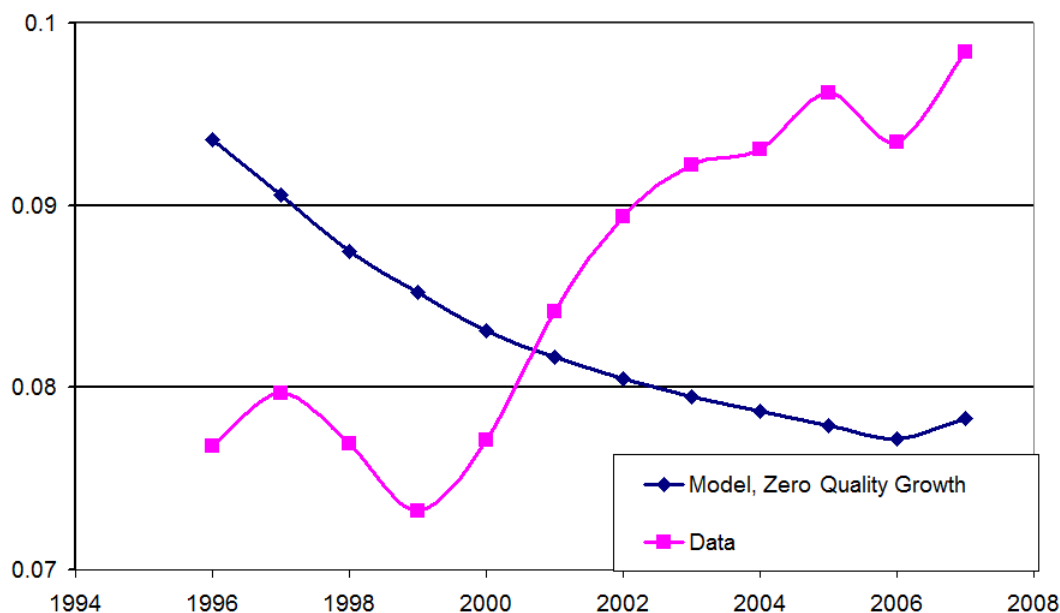
affect estimates of medical quality in two frameworks. In the first, medical consumption today affects survival rates today and tomorrow. In the second, there is heterogeneity within age, time groups with respect to non-medical factors ψ . In both cases, I use the synthetic data generated in these extended models to estimate medical quality using the methods developed in the paper. In both cases, these abstractions lead to potentially large differences in estimates of medical quality. In particular, the degree to which the baseline model differs from the model which generates the synthetic data determines the extent to which baseline estimates of medical quality differ from the actual values of medical quality. The models used to generate the synthetic data and more detailed results are presented in the appendix. I want to emphasize that both extensions are very simple, and are meant to provide coarse approximations of the impact of these abstractions on the estimation of medical quality. A complete treatment of these topics is beyond the scope of this paper.

In this paper, I've argued that the quality of medical goods and services has increased in the US between 1996 and 2007. One alternative hypothesis is that medical quality has not changed, and increases in medical purchases have been driven by changes in income and other factors. In principle, this hypothesis could be consistent with observed changes in medical purchases and survival rates. In particular, it could be the case that people are spending more because the marginal value of medical expenditures increases over time despite medical quality remaining constant. This increase in the marginal value of medical expenditures could be due to decreases in $\psi_{a,t}$ or increases in future utility $v_{a,t}$, possibly due to changes in income.

This hypothesis can be evaluated in the context of this model. To do this, I estimate the model assuming that quality remains constant across time. To be precise, I assume that medical quality parameters remain constant across time for

the three age groups. I place no restrictions on other parameters, and choose them in the same manner used previously. In the best fit scenario, model predictions for medical purchases are very inconsistent with data. In particular, the model predicts that, on average, medical expenditures as a share of income would decline over this period. I present this in Figure 1.12. The observed patterns in medical expenditures and survival rates are inconsistent with zero medical quality growth in this framework.

Figure 1.12: Counterfactual Medical Expenditure Share by Year, 25-84 Year Old Males



Validation

An important principle in developing structural models is validating the model. One common approach is to generate predictions from the model and compare them with the actual outcomes from an “out-of-sample” data source not used to estimate the parameters themselves. In this model, and many others, the model predictions depend on unobserved variables that are not directly measured, making such out-of-sample validation impossible. In particular, model predictions

depend on unobservable parameters $\psi_{a,t}$ and $A_{a,t}$. As a result, differences in these unobserved parameters, rather than the poor fit of the model itself, may explain any differences between the model's predictions and the actual outcomes of the out-of-sample population. Fang et al. (2007) develop an approach for validating such models for which out-of-sample validation is infeasible. They suggest determining whether or not the mechanisms associated with the unobservable parameters in the model are operative. In this setting, this means testing the qualitative predictions of the model. In particular, this means determining whether an individual's initial survival rate ψ and medical quality $A_{a,t}$ affect medical decisions in the predicted direction.¹⁴

Evidence on the effect of an individual's initial survival rate on medical demand will be taken from MEPS data. I will show that low self-reported health status leads to high medical demand after correcting for age, year and income. Individuals in the MEPS report health status ranging from excellent, corresponding numerically to 1, to poor, corresponding numerically to 5. One important caveat is that self-reported health status is not a perfect measure of an individual's initial survival rate. However, it is reasonable to believe that self-reported health status is an indicator of one's initial survival rate, and it is practical to use self-reported health status since initial survival rate is not observed. I use MEPS data to estimate the coefficients in the following equation:

$$x_{i,h} = \alpha_h d_{i,h} + \beta_0 a_{i,h} + \beta_1 a_{i,h}^2 + \beta_2 t_{i,h} + \beta_3 w_{i,h} + \epsilon_{i,h}$$

where i corresponds to the individual, h denotes an individual's health status ranging from 1 to 5, $d_{i,h}$ is a dummy for health status equaling 1 if health status equals h , and $\epsilon_{i,h}$ is a normally distributed error term which is i.i.d. across individuals.

¹⁴ Note that, by definition, the unobservable parameters affect survival rates in the predicted direction.

The results are presented in Table 1.2 The coefficients of interest are the α_h parameters. Results are in line with qualitative predictions of the model; as self-reported health status declines, the demand for medical goods and services increases. As a result, the model prediction that the demand for medical goods and services increases with ψ seems reasonable.

Table 1.2: Parameter Estimates: 95.0% CI in Parentheses

Health Status Parameters	
α_1	247.5 (200.1,295.0)
α_2	394.3 (344.3,444.3)
α_3	825.8 (772.7,879.0)
α_4	2536.1 (2465.2,2607.0)
α_5	6380.8 (6280.5,6481.2)
Other Parameters	
β_0	-45.2 (-47.6, -42.8)
β_1	1.04 (1.01, 1.06)
β_2	50.7 (46.6, 54.8)
β_3	2.09e-3 (1.51e-3, 2.67e-3)

Since measures of medical quality are not directly observable, evidence on the effect of changes in medical quality on medical demand will be taken from existing research on specific medical treatments. Evidence from specific medical treatments suggests that improvements in medical quality has two effects. First, quality improvements lead to increases in the number of individuals taking advantage of the type of treatment. Shapiro, Shapiro and Wilcox (2001) demonstrate that improved quality of cataract surgery led to higher demand for that surgery. Duggan and Evans (2005) demonstrate that improvement in the quality of antiretroviral drugs led to a sharp increase in the share of individuals with HIV who took one or more HIV drugs. Second, the introduction of higher quality medical treatments leads individuals to substitute new high quality treatments for older treatments.¹⁵ This trend is demonstrated in a number of studies, including

¹⁵ In other words, the introduction of new, high quality medical goods reduces the

Lucarelli and Nicholson (2009) for colorectal cancer patients, and Krone et. al. (2010) for stent patients. These studies, along with the previously mentioned evidence from MEPS, suggest that the mechanisms associated with the latent variables in this model are, in fact, operative.

1.6 Conclusion

In this paper, I estimate the quality of medical goods and services in the US. To do so, I develop and estimate a dynamic structural model of the medical decision. My estimates suggest that there have been large increases in the quality of medical goods and services in the US since 1996. One important implication of this finding is that the relative price of medical goods and services, adjusted for changes in quality, has actually declined over this period. Another important implication is that living standards have risen faster over this period than standard measures suggest.

The methods in this paper can be extended to address a large number of interesting problems. The one that is most interesting, in my view, is the comparison of health care systems across countries. A large variety of health care delivery systems are employed around the world. Many popular comparisons of the quality of medical care across countries focus on the relationship between medical spending and life expectancy. It is impossible, of course, to infer the quality of a health care delivery system using these two observations on their own. There is sure to be incredible value in effectively measuring the quality of these systems, and moving toward more efficient health care delivery systems, in the United States and around the world.

Chapter 2

ON THE ACCUMULATION AND DEPRECIATION OF HEALTH CAPITAL OVER THE LIFE CYCLE

2.1 Introduction

In the US and around the world, the share of resources allocated to medical goods and services is growing rapidly. Despite the great importance of the medical sector, little is known regarding the return to the medical goods and services that are purchased. Further, policy, through programs like Medicare and Medicaid, plays a large role in determining medical spending. In order to understand the effects of these policies, the medical decision process needs to be carefully modeled, and the model needs to be parameterized to be consistent with observed data.

In this paper, I develop a model of the accumulation and depreciation of health capital over the life cycle, similar to that of Grossman (1972). In this model, individuals allocate income to medical purchases, which affect their health capital stock, and non-medical consumption, which affect their period utility. An individual's health stock, in turn, affects the probability of surviving in each period of their life. The key parameters in this model determine the quality of medical purchases with respect to the accumulation of health capital, and the depreciation rate of health capital across an individual's life cycle. The key difficulty in inferring these parameters lies in the fact that an individual's survival rate in each period depends on the stock of health capital that was brought into the period, the quantity of medical purchases, and the quality of medical purchases. Because two of these variables are unobserved, survival rates are not enough to infer the unobserved parameters.

To overcome this problem, I model the demand for medical purchases. The key to this exercise is that survival rates in period t are increasing in medical

quality in period t , and decreasing in the depreciation rate of health capital in period $t - 1$,¹ while the demand for medical purchases in period t is increasing in both medical quality in period t in the depreciation rate of health capital in period $t - 1$. As a result, observations of medical purchases and survival rates in period t can be used to infer the the quality of medical care in period t and the depreciation rate of health capital in period $t - 1$.

The paper proceeds as follows. In section two, I present a basic version of the model. In section three, I discuss inference in the basic model. In section four, I present the full model. In section five, I present the data which will be used in the quantitative analysis. In section six, I discuss inference in the full model. In section seven, I present and discuss the results. In section eight, I discuss the sensitivity of the results to various modeling assumptions, and in section nine I conclude.

2.2 Basic Model

In this section, I develop a simple dynamic model of demand for medical goods similar to Lawver (2011), extended to allow for investment in health capital over the life cycle. The economy is populated by a cohort of ex-ante identical individuals which live three periods. Each individual is endowed with a lifetime stream of income and an initial health stock. Agents value medical consumption and non-medical consumption. Individuals value medical consumption because of the associated increases in the probability of surviving to the next period and in tomorrow's beginning of period health capital stock. Survival rates in each period depend on an individual's health capital at the beginning of the period and medical consumption. Individuals value non-medical consumption because it increases their period utility.

¹ The higher the depreciation rate in period $t - 1$, the "sicker" an individual will be in period t .

Demographics

Time is discrete, and indexed by a . There is one cohort of individuals which live a maximum of three periods, corresponding to $a = 0, 1, 2$. There are two sub-periods in each period, hereafter referred to as 'beginning' and 'end,' denoted by $i = 0, 1$. Subscripts denote the time period a and the superscript denotes that the sub-period within time period a . Health capital is the only variable which varies across sub-periods. Individuals are indexed by a , and are identical. Individuals are endowed with health capital H_0^0 at the beginning of period 0. In each period, individuals allocate income to purchases of medical goods and non-medical consumption. A fraction s_a survive to the next period.

Health Capital

Individuals invest in health capital over the life cycle. Health capital at the beginning of period at age a is denoted H_a^0 , and health capital at the end of the period is denoted H_a^1 . Health capital at the end of each period is a function of health capital at the beginning of each period as well as medical consumption m_a according to the following function g :

$$H_a^1 = g(H_a^0, m_a)$$

Function g is increasing in both arguments, and concave in medical consumption. I restrict function g , which I will call the health capital accumulation function, to be in the following form:

$$g(H_a^0, m_a) = H_a^0(1 + m_a)$$

At the end of each period, health capital depreciates. Health capital in the beginning of the next period is written as:

$$H_{a+1}^0 = (1 - \delta_a)H_a^1$$

where δ_a denotes the depreciation rate of health capital, which depends on the time period.

Medical Quality

Individuals value medical purchases x_a because of the associated increase in end of period health capital. Increasing end of period health capital has two effects. First, it increases the current period survival rate. Second, it increases health capital at the beginning of the next period contingent on survival. I define medical consumption m_a to be the product of the quantity of medical purchases x_a and the quality of medical purchases A_a . Medical quality, then, determines the rate at which each unit of medical purchases increases an individual's end of period health capital.

Preferences

Individuals value expected lifetime streams of non-medical consumption according to the following utility function:

$$\sum_a \beta^a f_a(\{m_j\}_{j=0}^{a-1}, H_0^0) u(c_a)$$

where $f_a(\{m_j\}_{j=0}^{a-1})$ denotes the probability that an individual survives to age a as a function of medical consumption before age a and initial health capital H_0^0 , and u is the period utility function, which is increasing and concave. The utility from death is normalized to zero. I restrict u to be in the following form:

$$u(c_a) = \log(c_a) + b$$

where b is the constant term in the flow utility function. This term is important in models with endogenous survival rates. Since the level of the value of death is normalized to zero, the level of utility during while alive is an important determinant of the optimal level of medical purchases.²

² For further discussion, see Hall and Jones (2007)

Survival Function

The probability that an individual survives to the next period is a function of an individual's end of period health capital. An individual's period mortality rate is the inverse of end of period health capital. An individual's period survival rate, then, is written:

$$s_a = 1 - \frac{1}{H_a^1}$$

Budget

Individuals are endowed with a lifetime stream of income, with period income endowment written y_a . In each period, individuals allocate income to medical purchases x_a and non-medical consumption c_a . The relative price of medical purchases is the same in all periods, and is denoted p .

Individual Decision Problem

The individual decision problem is written as follows:

$$V_a(H_a^0) = \max_{x_a, c_a} [u(c_a) + \beta s_a V_{a+1}(H_{a+1}^0)]$$

$$\text{subject to: } c_a + px_a = y_a$$

$$H_a^1 = g(H_a^0, A_a x_a)$$

$$H_{a+1}^0 = (1 - \delta_a) H_a^1$$

$$s_a = 1 - \frac{1}{H_a^1}$$

2.3 Inference in the Basic Model

The key exercise here is to use the model to infer unobserved parameters using observations of medical purchases x_a and survival rates s_a . The unknown parameters in this model determine the life cycle profile of medical quality A_a , health capital depreciation rate δ_a , and beginning of period health capital H_a^0 . Note that, by construction, the life cycle profile of H_a^1 can be inferred directly by

observations s_a . Since this is a three period model, health capital in the final period is irrelevant to the decision process, and the depreciation rate of health capital in the second to last period is also irrelevant to the decision process. Since medical consumption and health capital do not enter into the period utility function, individuals will make no medical purchases in the final period. The relevant exercise in this simple setting, then, is to use observations of x_a and s_a in periods 0 and 1, along with observations of income and prices, to infer H_a^0 and A_a in periods 0 and 1, and δ_0 .

The Mechanics of Inference

The key to inference in this setting is working backwards. In period 2, independent of an individual's health capital, individuals will allocate all of their income to non-medical consumption because medical purchases are not valuable in the final period of life. As a result, $V_2(H_2^0) = u(y_2)$ for all H_2^0 . Since $V_2(H_2^0)$ does not depend on H_2^0 , δ_1 does not affect the individual's decision problem. Further, by definition, $H_1^1 = 1/(1 - s_1)$. The two relevant unobserved parameters in period 1, then, are H_1^0 and A_1 .

It is straightforward to infer H_1^0 and A_1 from observation of x_1 and s_1 . The key idea is that s_1 , taking x_1 as given, is increasing in both H_1^0 and A_1 , while the optimal level of x_1 is decreasing in H_1^0 , and increasing in A_1 . As a result, there is a single pair (A_1, H_1^0) such that model predictions for survival rates and medical purchases match observations of these variables. One important thing to note is that this relationship between model parameters and the medical purchase decision is consistent with the data.³ Once A_1 is inferred, $V_1(z)$ can be calculated for all possible values of beginning of period 1 health capital, denoted z in the function.

³ For more detail, see Lawver (2011)

Once H_1^0 and A_1 are inferred, it is straightforward to infer H_0^0 , A_0 , and δ_0 from observation of x_0 and s_0 . The depreciation rate in period 0 δ_0 can be calculated directly once H_1^0 has been inferred since H_0^1 is known. By definition, $\delta_0 = 1 - H_1^0/H_0^1$. Once δ is inferred, H_0^0 and A_0 can be inferred in the same fashion as H_1^0 and A_1 . Once again, taking all other parameters as fixed, there is a single pair (A_0, H_0^0) such that model predictions for match observations for survival rates and medical purchases.

This approach is similar to the approach employed in Lawver (2011) in a model in which medical purchases affect an individual's period survival rate, but have no effect on an individual's period survival in the next period. This paper extends the methods of Lawver (2011) in order to infer the life cycle profile of health capital depreciation rates in a model with health capital investment.

A Numerical Example

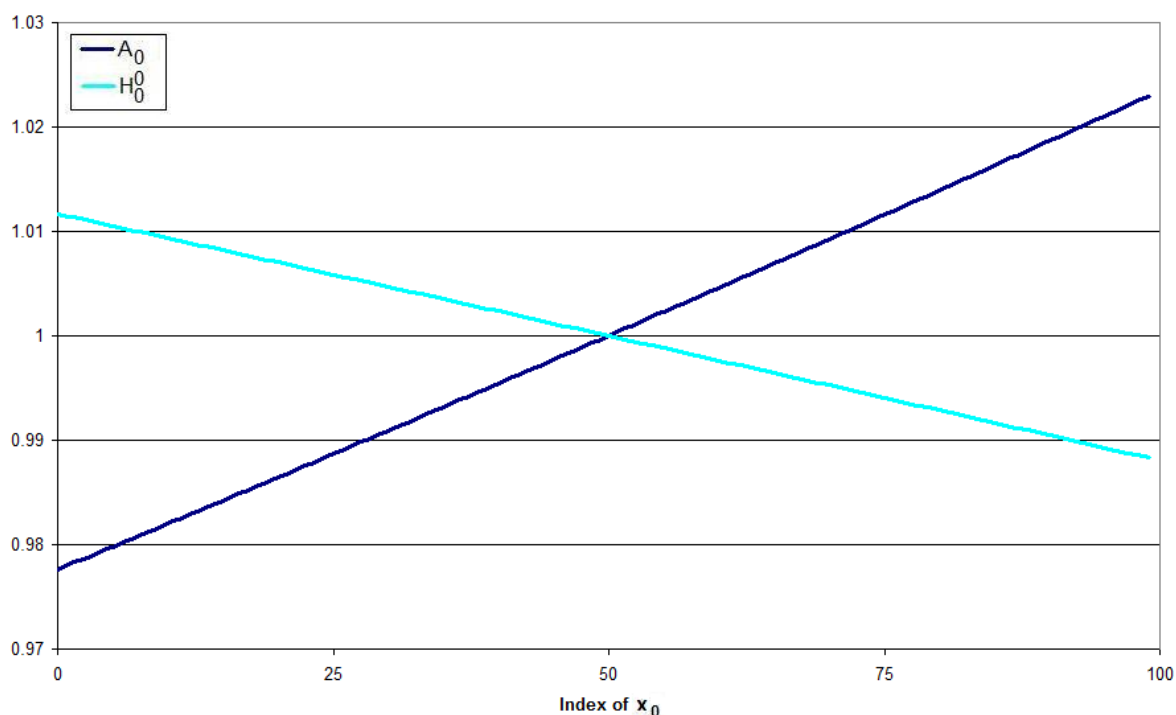
Here, I present an example to detail the mapping between observations and model parameters numerically. To do so, I infer model parameters for a variety of observations of medical expenditure decisions and survival rates in periods 0 and 1. I allow the observation of one variable to vary at a time in order to present the effect that changes in observations have on changes in the inferred model parameters.

In the baseline case, I choose $y_a = 50000$, $p = 1$, $\beta = .96$, $b = 10$, observed survival rates are $s_0 = s_1 = 0.98$, and observed medical purchases are $x_0 = x_1 = 5000$, and $x_2 = 0$.⁴ In the following numerical exercises, I will allow each of x_0 , x_1 , s_0 , and s_1 to vary. In each figure, the variable on the x-axis will be an index of the variable which will be varied in the exercise, with index value 50 corresponding to the baseline observation of the variable. The variable on the

⁴ Recall that individuals do not value medical purchases in period two, because they do not affect lifetime utility.

y-axis corresponds to the inferred value of the parameter relative to the baseline parameter value.

Figure 2.1: Inferred Model Parameters Relative to Baseline Estimate For Variation in x_0

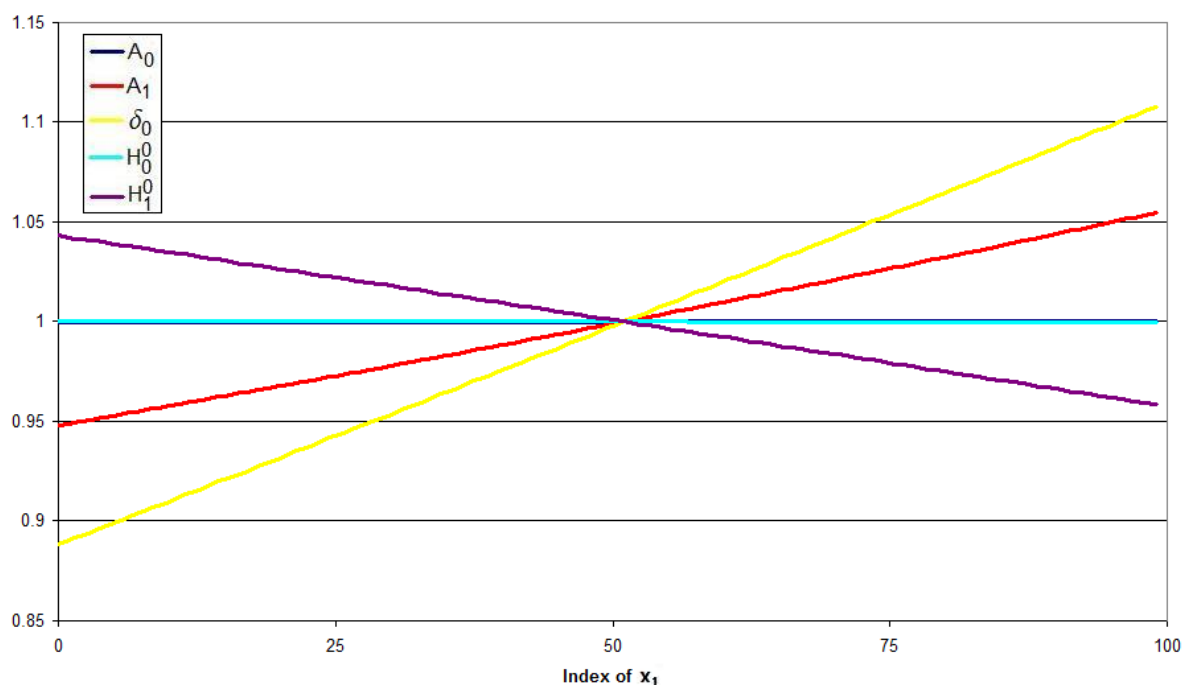


In the first numerical exercise, I allow x_0 to vary between 4500, corresponding to an index value of 0, and 5500, corresponding to an index value of 100, and keep observations of the other three variables fixed. As shown in the figure, an increase in the observation of x_0 leads to an increase in the inferred value of A_0 , a decrease in the inferred value of H_0^0 , and no change in the inferred value of other parameters. Parameters A_1 and H_1^0 are inferred directly from period 1 observations, therefore changes in period 0 observations have no effect on them. Parameter δ_0 is inferred from period 1 observations and s_0 . This implies that changes in x_0 have no effect on the inferred value of δ_0 .

An increase in x_0 implies that the marginal value of medical spending

increased at the baseline medical spending level. Since nothing in periods one or two changed, this must have been generated by either an increase in A_0 , a decrease in H_0^0 , or both. An increase in A_0 without a decrease in H_0^0 would lead to an increase in the equilibrium period zero survival rate, and a decrease in H_0^0 without an increase in A_0 would lead to a decrease in the equilibrium period zero survival rate,⁵ therefore both A_0 must have increased and H_0^0 must have decreased in order to generate the increase in period zero medical spending without any change in the period zero survival rate.

Figure 2.2: Inferred Model Parameters Relative to Baseline Estimate For Variation in x_1



In the second numerical exercise, I allow x_1 to vary between 4500, corresponding to an index value of 0, and 5500, corresponding to an index value of 100, and keep observations of the other three variables fixed. As shown in the figure, an increase in the observation of x_1 leads to increases in the inferred

⁵ Both can be shown using a simple revealed preference argument.

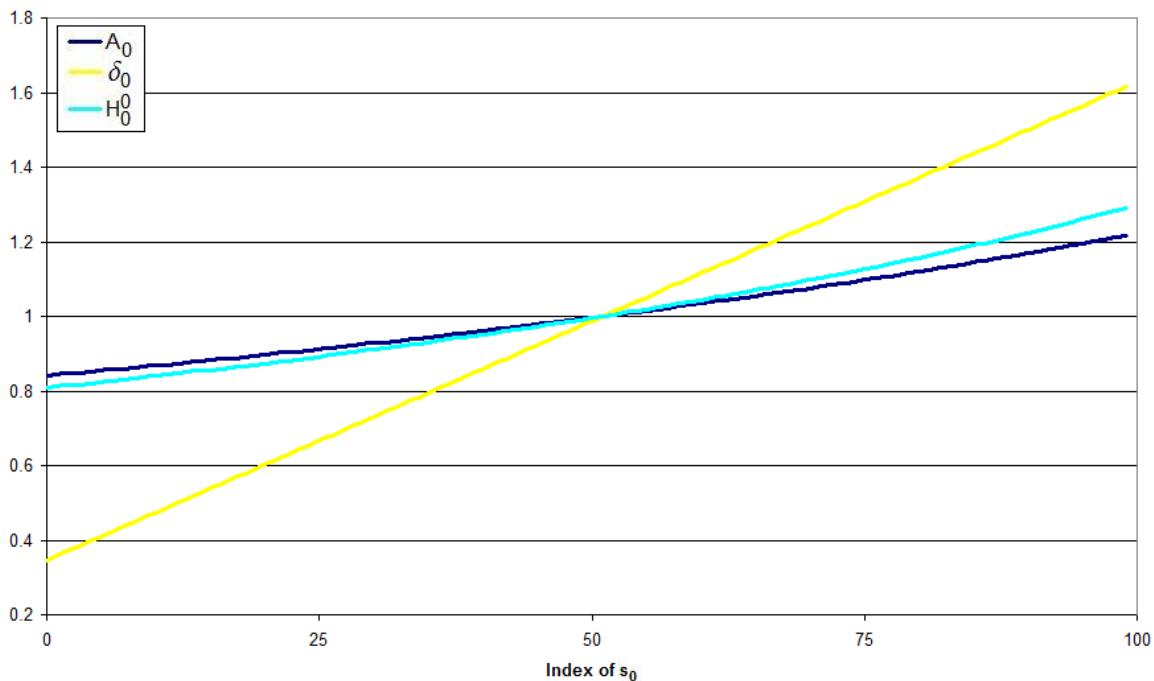
values of A_1 , δ_0 , and H_0^0 , and decreases in the inferred values of H_1^0 and A_0 . The changes in the inferred values of A_1 and H_1^0 are straightforward, and generated in a similar fashion to the changes in A_0 and H_0^0 discussed in the first numerical exercise. A decrease in H_1^0 without a change in H_1^0 implies that the inferred value of δ_0 increased.

The changes in the inferred values of H_0^0 and A_0 are very small, and are not quite as straightforward. Here, two things which affect the value of medical spending in period zero are changed. If the value of medical spending had changed, then a change in x_0 would be expected. Parameters A_0 and H_0^0 , then, must change in order to generate no change in x_0 to counteract the effects of other factors on the value of period one medical spending. First, an increase in medical spending in period one implies that non-medical consumption decreased in period one, which implies that the value living to period one declined, decreasing the marginal value of medical spending in period one. Second, an increase in δ_0 increases the value of medical spending in period zero.⁶ As shown in the figure, there is a very small increase in the inferred values of A_0 and a very small decrease in the inferred value of H_0^0 , implying that the second effect dominated the first only slightly.

In the third numerical exercise, I allow s_0 to vary between .975, corresponding to an index value of 0, and .985, corresponding to an index value of 100, and keep observations of the other three variables fixed. As shown in the figure, an increase in the observation of x_0 leads to increases in the inferred values of A_0 , H_0^0 , and δ_0 , and no change in the inferred value of other parameters. Parameters A_1 and H_1^0 are inferred directly from period 1 observations, therefore changes in period 0 observations have no effect on them. A change in s_0 , by definition, increases H_0^1 without a change in H_1^0 , which implies that the inferred

⁶ EXPLAIN

Figure 2.3: Inferred Model Parameters Relative to Baseline Estimate For Variation in s_0

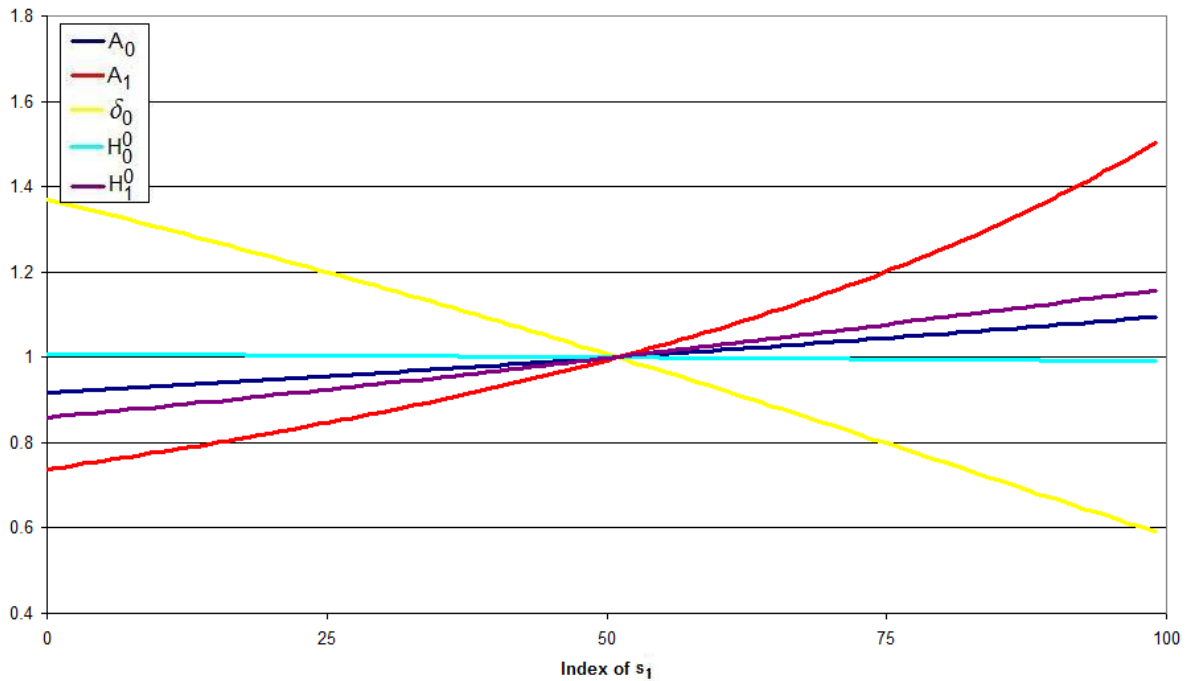


value of δ_0 increased.

Since x_0 is fixed, an increase in s_0 implies that either A_0 increased, H_0^0 increased, or both. An increase in A_0 without an increase in H_0^0 would lead to an increase in x_0 , and an increase in H_0^0 without an increase in A_0 would lead to a decrease in x_0 , therefore both must have increased in order to generate an increase in s_0 without a change in x_0 .

In the fourth numerical exercise, I allow s_1 to vary between .975, corresponding to an index value of 0, and .985, corresponding to an index value of 100, and keep observations of the other three variables fixed. As shown in the figure, an increase in the observation of x_1 leads to increases in the inferred values of A_0 , A_1 , and H_1^0 , and decreases in the inferred values of H_0^0 and δ_0 . The changes in the inferred values of A_1 and H_1^0 are straightforward, and generated in

Figure 2.4: Inferred Model Parameters Relative to Baseline Estimate For Variation in s_1



a similar fashion to the changes in A_0 and H_0^0 discussed in the third numerical exercise. An increase in H_1^0 without a change in H_1^0 implies that the inferred value of δ_0 decreased.

The changes in the inferred values of H_0^0 and A_0 are generated by similar forces as in the second numerical exercise. Once again, two things which affect the value of medical spending in period zero change. First, an increase in the period one survival rate implies that the value living to period one increased because of the increase in the expected utility of surviving to period two. Second, a decrease in δ_0 decreases the value of medical spending in period zero. In this cases, the result of these effects was an decrease in the value of medical spending, meaning an increase in A_0 and a decrease in H_0^0 are necessary in order to generate no change in observations of x_0 and s_0 .

2.4 Full Model

In this section, I extend the model developed in section two in order to study the accumulation and depreciation of health capital over the life cycle in the US. I extend the model along three dimensions: individuals live at most fifteen periods instead of three, corresponding to the seventy-five year time horizon between ages 25 and 100, individuals pay for a share θ_a of medical expenditures out of pocket, and individuals can accumulate savings, denoted k_a , over their life cycle in order to smooth their lifetime non-medical consumption stream. The economy is populated by a cohort of ex-ante identical individuals which live at most fifteen periods, corresponding to $a = 0, 1, \dots, 14$. Each individual is endowed with a lifetime stream of income and an initial health stock H_0^0 , and no initial assets.

Budget

Individuals are endowed with a lifetime stream of income, with period income endowment written y_a . In each period, individuals allocate their income endowment and savings income to medical purchases x_a , non-medical consumption c_a , and tomorrow's savings s_{a+1} . The relative price of medical purchases is denoted p , and the net return on savings is denoted R . Individuals pay a fraction θ_a of their medical expenditures out of pocket, in line with the fact that a large portion of medical expenses are financed indirectly via public and private insurance. Savings is constrained to be non-negative in each period, and accidental bequests are not redistributed.

Individual Decision Problem

The individual decision problem is written as follows:

$$V_a(H_a^0, k_a) = \max_{x_a, c_a, k_{a+1}} [u(c_a) + \beta s_a V_{a+1}(H_{a+1}^0)]$$

$$\text{subject to: } c_a + \theta_a p x_a + k_{a+1} = y_a + R k_a$$

$$k_{a+1} \geq 0$$

$$H_a^1 = g(H_a^0, A_a x_a)$$

$$H_{a+1}^0 = (1 - \delta_a) H_a^1$$

$$s_a = 1 - \frac{1}{H_a^1}$$

2.5 Data

The goal of this exercise is to infer the life cycle profile of the quality of medical purchases A_a , and the depreciation rate of health capital δ_a in the US. To do so, I will use data on the life cycle profile of medical purchases, survival rates, and other variables for males⁷ in the US between 1996 and 2007 to construct an average life cycle profile. In order to do this exercise, three data sources are used. The data used here are annual and come from the Medical Expenditure Panel Survey (MEPS), the Bureau of Labor Statistics (BLS) and the Social Security Administration (SSA). This data is used to construct observations of survival rates s_a , medical purchases x_a , co-insurance rates θ_a , and income endowments y_a for each 5-year age group from 25-99,⁸ and the relative price of medical purchases p . BLS data is used to construct the relative price of medical purchases by averaging the relative price of medical purchases between 1996 and 2007.

The MEPS reports data on income, medical expenditures, and out-of-pocket medical expenditures at the individual level for males 25-84. The

⁷ Males are studied here for simplicity, as their medical decisions of males are not affected by pregnancy.

⁸ 25-29 year olds, 30-34 year olds, etc.

also report average health insurance premium payments made by employees. For individuals under 65, an individual's income endowment is defined to be their income, as reported by MEPS, minus the average health insurance payment made by employees. For individuals 65-84, the income endowment is defined to be income as defined in MEPS. I use the individual-level data to construct age-level data in each period by averaging across individuals in the age group in all time periods. To calculate the average co-insurance rate θ_a that individuals pay, I calculate the share of total medical expenses that are paid by each group. Overall, out-of-pocket payments make up a small fraction of medical expenses, and generally declines with age. This pattern is shown in Figure 2.5. Income endowments and co-insurance rates for individuals 85 to 99 are chosen to be equal to their corresponding values for 80-84 year olds, because MEPS data is not available for these age groups. Medical purchases are calculated by determining average medical spending in each group, and dividing by the average relative price of medical purchases p .

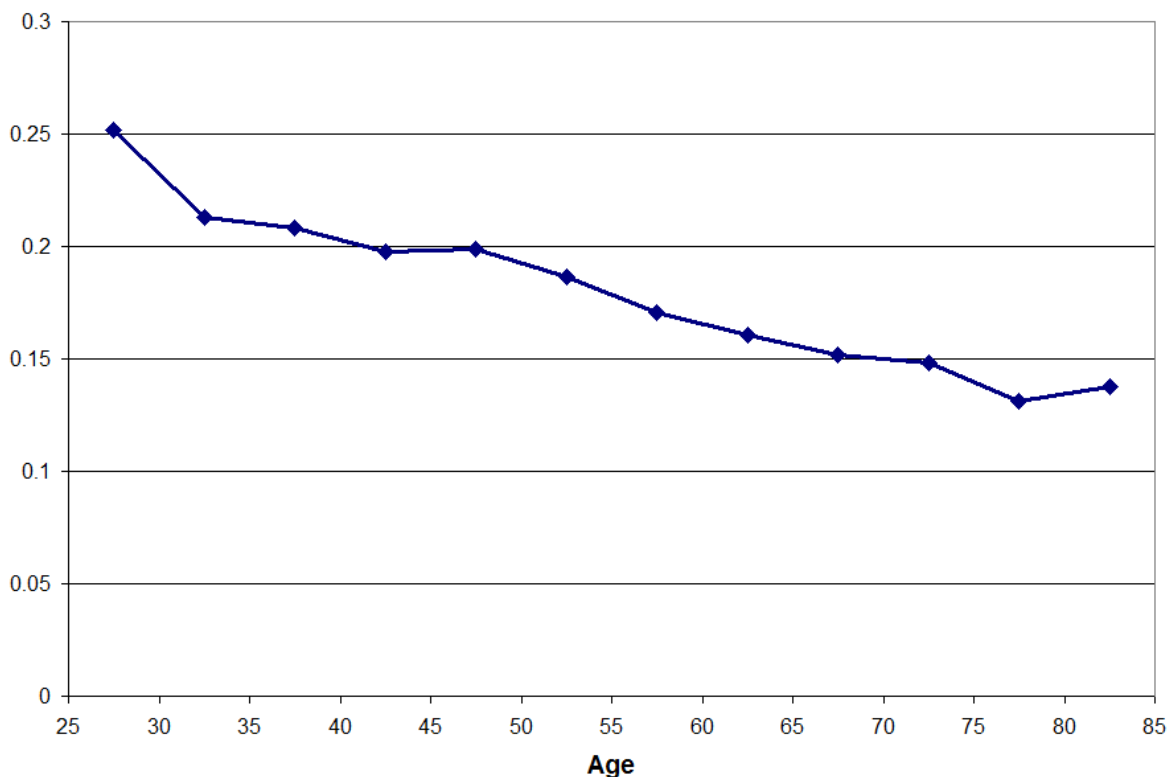
The SSA reports mortality rates at every age for 1990, 2000, and 2010. I construct mortality rates in years that are not reported using linear interpolation. The mortality rate s_a is defined to be the probability that an survives in each of the years making up period a . For $a = 0$, this corresponds to the probability of surviving from age 25 to age 30. Figure 2.6 shows the life cycle profile of survival rates over this period.

Figure 2.7 shows the life cycle profile of medical expenditures relative to income. As shown in the figure, the share of income devoted to medical expenditures rises sharply with age.

2.6 Inference in the Full Model

The unknown parameters in this model determine the life cycle profiles of the quality of medical purchases in the accumulation of health capital A_a and of the

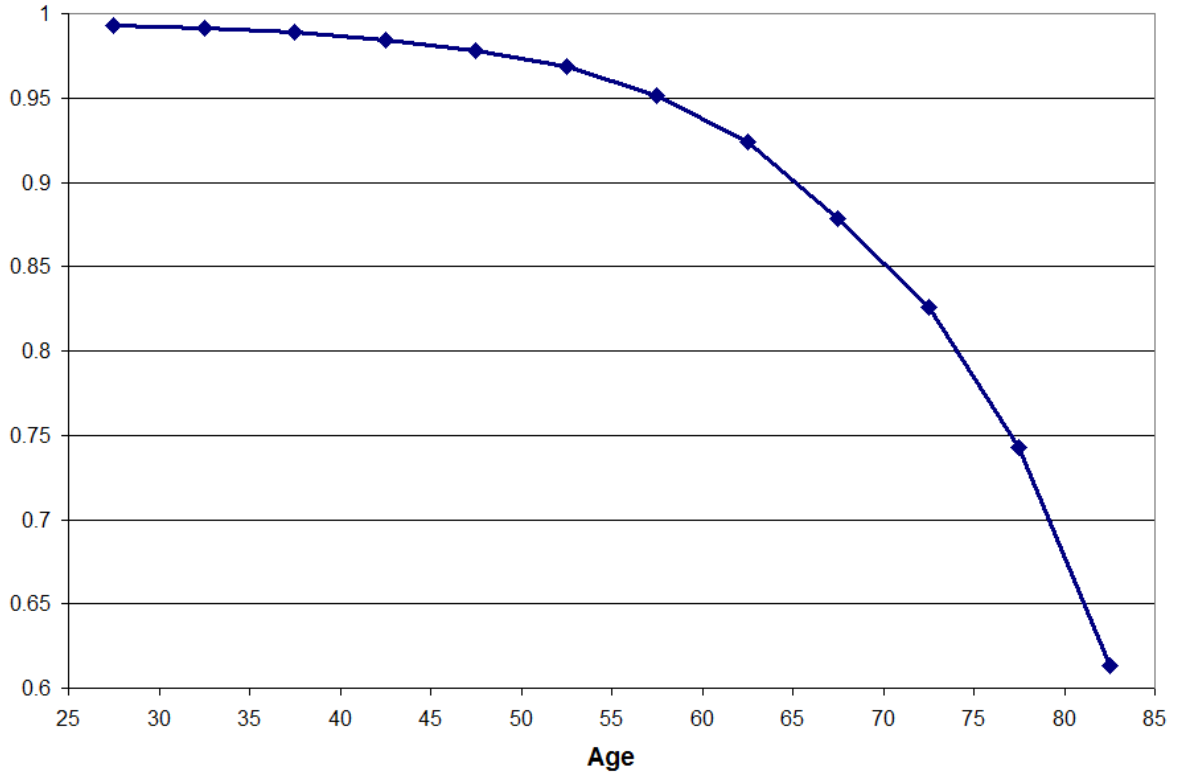
Figure 2.5: Co-Insurance Rate by Age Group



depreciation rate of health capital δ_a , the constant term in the period utility function b , the discount rate β , and the net return on assets R . I will assume that the yearly discount rate is .96, implying that $\beta = .96^5$. I will assume that $R = 1/\beta - 1$.

The key exercise here is to use the model to infer the life cycle profiles of the unobserved parameters using observations of the life cycle profiles of medical purchases x_a and survival rates s_a . The unknown parameters in this model determine the life cycle profile of medical quality A_a , health capital depreciation rate δ_a , and beginning of period health capital H_a^0 . The key to this exercise, as in the basic model, is to work backwards. In the final period, an individual's health capital stock does not affect their decisions, and therefore the depreciation rate of health capital in the second to last period does not affect decisions. As a result, it

Figure 2.6: Survival Rate by Age Group

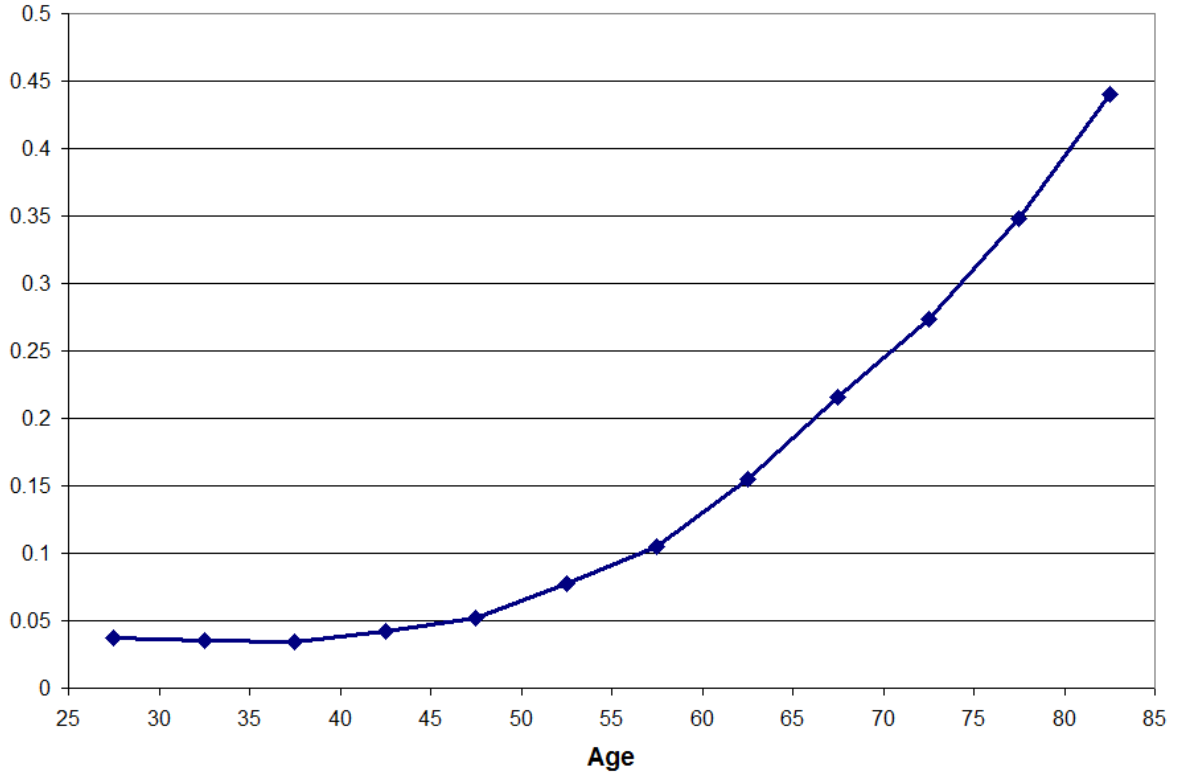


is straightforward to infer medical quality and beginning of period health capital in the final period, and therefore the depreciation rate of health capital in the second to last period. Given that these parameters have been inferred, it is straightforward to work one step backward. I will detail these steps in this section.

Outline of procedure

Here, I will outline the procedure used to infer model parameters over the life cycle. First, I guess the value of the constant term in the period utility function b . Then I infer all other model parameters, taking b as given. Then I calculate the implied value of statistical life for 35-44 year olds, and use this information to update the guess of b . I repeat this process until the value of statistical life in the model is consistent with the estimate in Aldy and Viscusi (2008).

Figure 2.7: Medical Expenditures Relative to Income by Age Group



To infer model parameters other than b , taking the value of b as given, I proceed iteratively. In the first step, I guess the life cycle profile of savings, A_{11} , and δ_{10} . I use this to calculate the value of living to period 12. Then, working backwards, I infer model parameters starting with A_{11} , H_{11}^0 , and δ_{10} . Then, I check the intertemporal Kuhn-Tucker conditions to see if the guessed savings decision is consistent with optimal decision making. If it isn't, I update the savings decision rule so the intertemporal Kuhn-Tucker conditions are satisfied.⁹ I also check whether the guessed values of A_{11} and δ_{10} are consistent with the inferred values of the same parameters. I update the guess of A_{11} and δ_{10} , as well as the guess for the savings profile, until this process converges.

⁹ Note that the only complication arises because asset holdings are constrained to be non-negative

Decision Rule Computation

The basic strategy used throughout this procedure in each stage of this procedure is to guess parameters, compute medical purchase decision rules as a function of the parameters, and update the guess of the parameters based on the comparison of the implied decision rules with the data. Here, I will detail the strategy used to compute medical decision rules.

One complication in this exercise is that the value function depends on the stock of health capital that individuals bring into each period, and therefore the medical purchase decision depends on the marginal value of increases in the health capital stock. This type of problem is typically solved by computing the value function over a wide range of values of the health capital stock. I take another approach. The key to my approach is that parameters are inferred starting in the final period. In period t , given that all δ_t and all future parameters and decision rules are known, it is straightforward to calculate the marginal value of medical purchases as a function of A_t and H_0^t without differentiating the value function with respect to the health capital stock. The key to this is that, in period t , the probability of surviving to each time period can be written as a function of today's beginning of period health capital stock, today's medical consumption, all future medical consumption levels, and health capital depreciation rates starting period t . This is because s_{t+1} depends on m_{t+1} and H_{t+1}^0 , which depends on H_t^0 , m_t , and δ_t . Extending this forward, one can write s_{t+i} as a function of H_t^0 , $\{\delta_{t+j}\}_{j=0}^{i-1}$, and $\{m_{t+j}\}_{j=0}^i$. For convenience, let $h_{ti}(H_t^0, \{\delta_{t+j}\}_{j=0}^{i-1}, \{m_{t+j}\}_{j=0}^i)$ be the function describing survival rates in period $t+i$ as described previously. The marginal value of a unit of medical consumption in period t , then, can be written as:

$$\sum_{i=0:T-t} \frac{\partial h_{ti}}{\partial m_t} \beta^{i+1} u(c_{t+i+1})$$

where each term in the summation describes the marginal increase in discounted

period $t + i + 1$ utility with respect to medical consumption¹⁰ in period t . From here, it is straightforward to solve for the period t allocation which solves the consumer's maximization problem, taking current and future period parameters as given.

Value of Statistical Life

Following Hall and Jones (2007), the parameter b is chosen to match an estimate of the value of a statistical life. In particular, I will choose b so that 34-44 year olds value their lives at 9.9 million dollars,¹¹ based on the estimate from Aldy and Viscusi (2008).¹² The value of a statistical life is the dollar value of an individual's expected utility stream. Following Kniesner, Viscusi, and Ziliak (2006), the value of a statistical life for 35-44 year-olds, which I will call VSL , is calculated as follows:

$$VSL = \frac{1}{2} \frac{V_2(H_2^0, k_2)}{u'(c_2)} + \frac{1}{2} \frac{V_3(H_3^0, k_3)}{u'(c_3)}$$

where V_a corresponds to the value function at age a . Recall that the value of a statistical life is the dollar value of an individual's expected utility stream. The value function, evaluated at the realized values of health capital and assets, is the individual's expected utility stream. To calculate the dollar value of the expected utility stream, it is divided by $u'(c_a)$, the marginal utility of wealth.

Model parameters for 85-99 year olds

One complication in this procedure is that MEPS data does not include observations for these age groups. It is important to include these groups because the decisions of younger individuals depend on the value of living to these ages. Because of this, I assume that δ_{11} , δ_{12} , and δ_{13} are equal to δ_{10} , ie that the health

¹⁰ One can easily convert this in to the marginal increase in discounted period $t + i + 1$ utility with respect to medical purchases.

¹¹ There is considerable variation in estimates of the value of a statistical life. For a survey, see Viscusi and Aldy (2003). I will discuss the sensitivity of results to the choice of the value of a statistical life in Section 8.

¹² Their estimate corresponds to the value of life for individuals in this age group in 2000, which is roughly the midpoint of my sample.

capital depreciation rate is constant after ages 75-79. Given this assumptions, it is straightforward to calculate H_{12}^0 , H_{13}^0 , and H_{14}^0 using observations of survival rates. The proceeds iteratively. In the first stage, I guess δ_{10} , which determines the health capital depreciation rate for the older groups. Then, I choose parameters A_{12} , A_{13} , and A_{14} so that model predictions for survival rates are consistent with the data for these age groups. Then, I infer model parameters for individuals under 85. Then, I update the guess of δ_{10} , and repeat this procedure until convergence.

Model parameters for 25-84 year olds

The procedure to determine model parameters for 25-84 year olds works backwards. To infer parameters in period t , taking δ_t and all future parameters as given, as proceed as follows. First, I guess \tilde{A}_t . Then, I calculate the \tilde{H}_t^0 which solves $H_t^1 = g(\tilde{H}_t^0, \tilde{A}_t x_t)$, where x_t denotes the observation of medical purchases in the data. I then calculate decision rules as a function of \tilde{A}_t and \tilde{H}_t^0 , and compare the medical purchase decision implied by the model with the medical purchase decision in the data. Based on the decision rule implied by my guess of \tilde{A}_t , I update my guess of \tilde{A}_t , and repeat this process until it converges.

2.7 Results

In this section, I present and discuss the results of the main exercise. In particular, I will report the life cycle profiles of the quality of medical care and of the depreciation rate of health capital. Figure 2.8 shows the life cycle profile of δ_a . As shown in the figure, the depreciation rate of health capital is generally increasing over the life cycle. One surprising result is that the depreciation rate. This result is not so surprising once one takes into account that the 5-year mortality rate between ages 65-69 is 3.8 times higher than the mortality rate between ages 50-54, while the mortality rate between ages 80-84 is 3.2 times higher than the mortality rate between ages 65-69.

Figure 2.8: Life Cycle Profile of δ_a

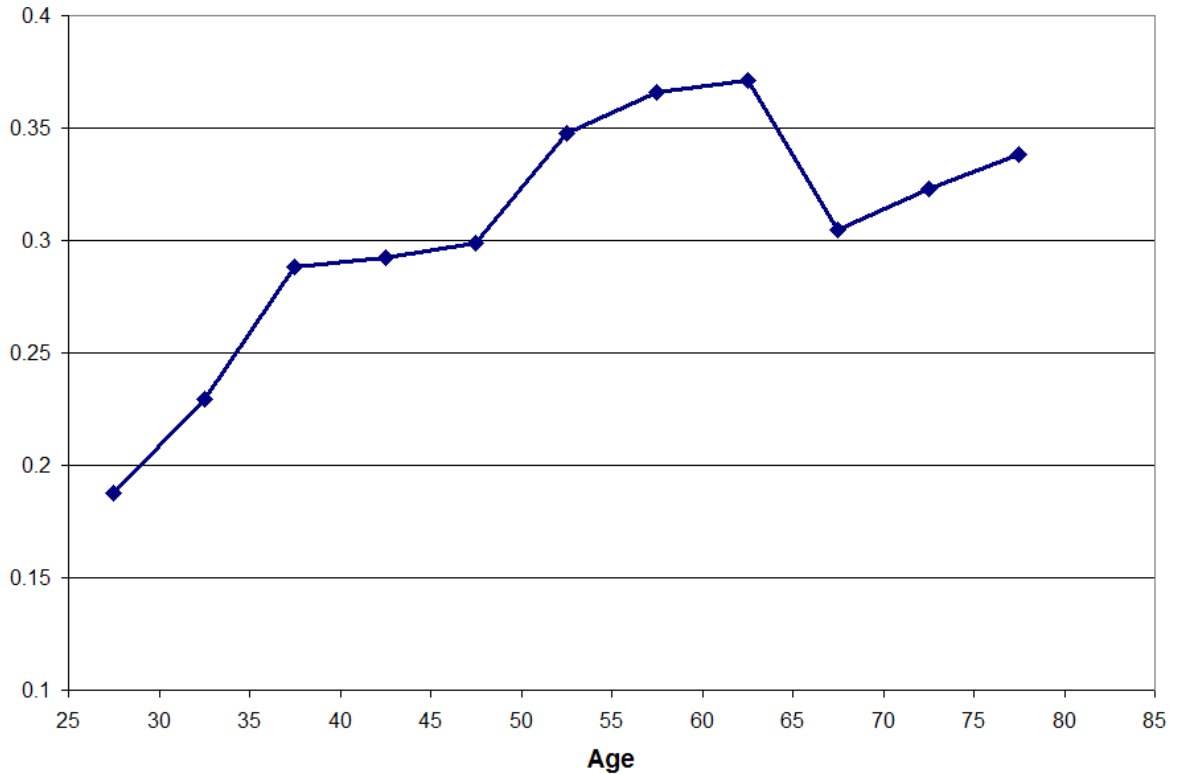
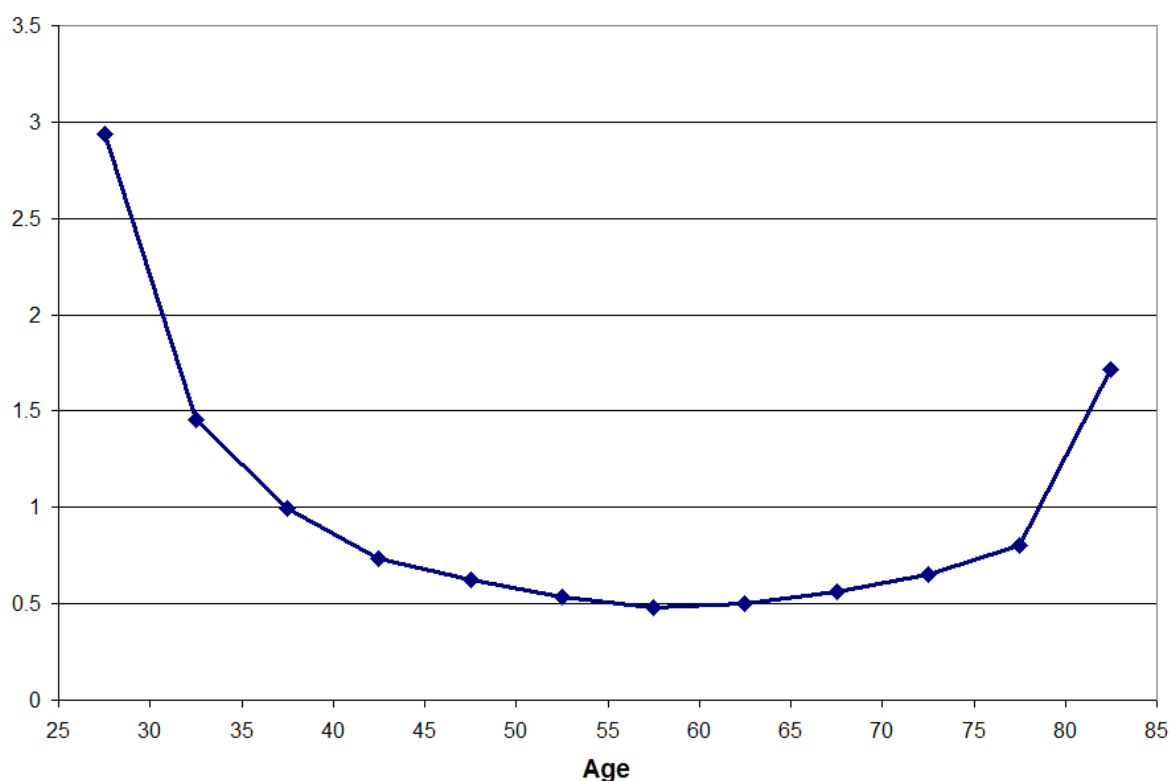


Figure 2.9 shows the life cycle profile of A_a , normalized so that the average value of A_a equals one. As shown in the figure, the quality of medical care is highest for 25-29 year olds, almost three times higher than average. Medical quality declines steady until ages 55-59, and rises afterward, rising most sharply for 80-84 year-olds. This result is likely due to variation in the types of treatment that individuals purchase over the life cycle, and variation in the quality of each type of treatment. According to MEPS data, the highest portion of expenditures for 25-44 year-old males are for trauma-related conditions. For 45-64 year-olds, the highest portion of expenditures are for cancer, and for 65-84 year-olds the highest portion of medical expenditures are for heart conditions. More work is needed to decompose the quality of medical care in general for each age group into the

quality of medical care for each type of treatment for each age group.

Figure 2.9: Life Cycle Profile of A_a



2.8 Sensitivity

In this section, I report the inferred model parameters for a variety of specifications of the model. The goal of this exercise is to understand the importance of various modeling assumptions in the mapping between the data and the model parameters. In particular, I explore the extent to which the specification of the period utility function and the health capital accumulation function affect the results. I also explore the extent to which the targeted value of statistical life effects results. I will focus on the effect that changes in the specification of the model have on the inferred values of medical quality, as these values are much more sensitive to the changes that I consider than the inferred values of the depreciation

rate of health capital.

I will consider period utility functions in the following form:

$$u(c_a) = \frac{c_a^{1-\gamma}}{1-\gamma} + b$$

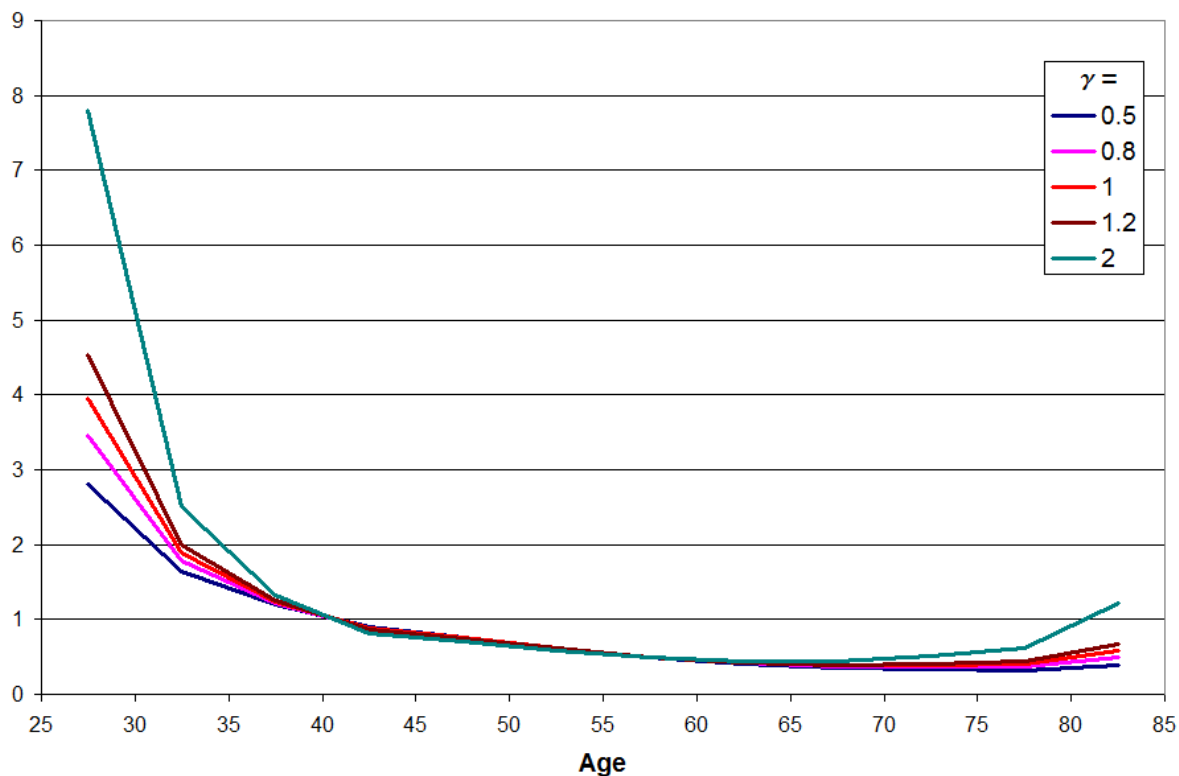
Recall that the baseline specification corresponds to the case that $\gamma = 1$. In Figure 2.10, I report results from the main quantitative exercise in the case that γ equals .5, .8, 1.2, and 2, and compare them to the baseline case in which $\gamma = 1$. I scale the reported values of medical quality so that the average medical quality in the baseline case is equal to one. As shown in the figure, the inferred values of the quality of medical care are most sensitive at ages 25-29 and 80-84, and least sensitive between ages 40 and 70. In general, as shown in the figure, a higher γ implies that medical quality must be higher. The reason for this is that the higher γ is, the slower the marginal utility of non-medical consumption declines, and therefore, for a fixed level of consumption, the higher the quality of medical care must be in order to equate the marginal value of medical and non-medical consumption.

I will now consider health capital accumulation functions in the following form:

$$g(H_a^0, m_a) = H_a^0(1 + m_a^\eta)$$

Recall that the baseline specification corresponds to the case that $\eta = 1$. In Figure ??, I report results from the main quantitative exercise in the case that η equals .8, and .9, and compare them to the baseline case in which $\eta = 1$. I scale the reported values of medical quality so that the average medical quality in the baseline case is equal to one. As shown in the figure, changes in η have a large effect on the inferred values of medical quality for every age group. For $\eta = .9$, the inferred values of medical quality are roughly doubled for all age groups, and for $\eta = .8$, the inferred values of medical quality are roughly quintupled for all age

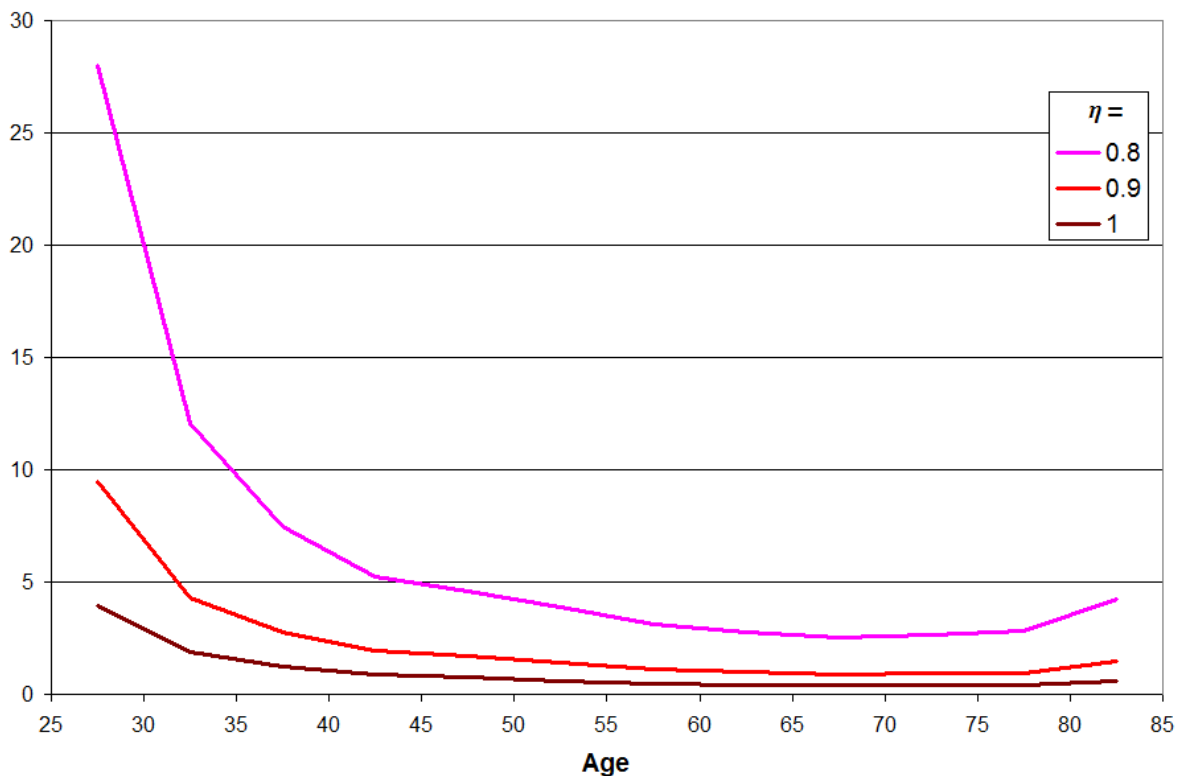
Figure 2.10: Inferred Medical Quality Profile For Variation in γ Relative to Average Medical Quality for $\gamma = 1$



groups. The reason for this is that the marginal increase in the survival rate with respect to medical consumption is decreasing in η . Then, for a fixed level of medical purchases, a lower value of η implies that a higher level of medical quality is necessary in order for the marginal value of medical purchases to be equal to the marginal value of non-medical consumption.

In Figure 2.11, I investigate the extent to which changes in η scale the life cycle profile of medical quality by plotting the quality of medical care relative to the average quality of medical care for each η . As you can see in the figure, the life cycle profiles look almost identical after each profile is normalized so the average value is equal to one. This implies that changing η , over this range, effectively

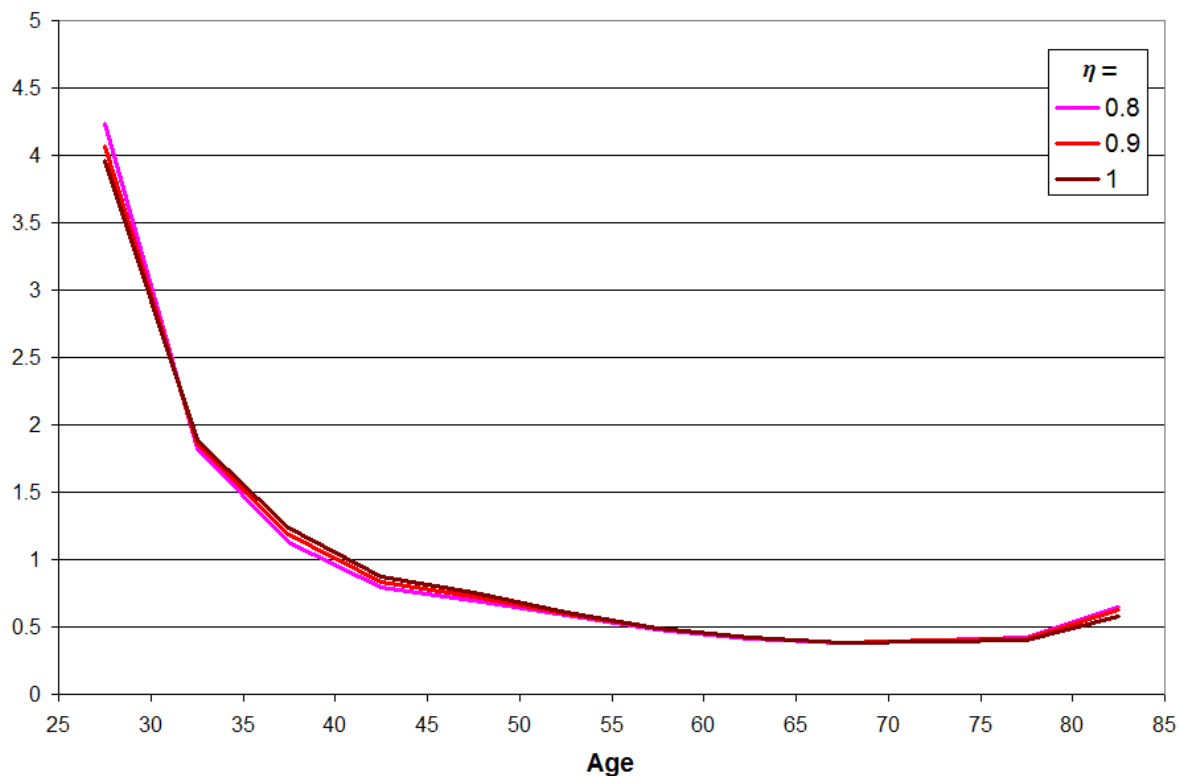
Figure 2.11: Inferred Medical Quality Profile For Variation in η , Relative to Average Medical Quality for $\eta = 1$



scales the life cycle profile of the quality of medical care, while having a minor impact on the its shape.

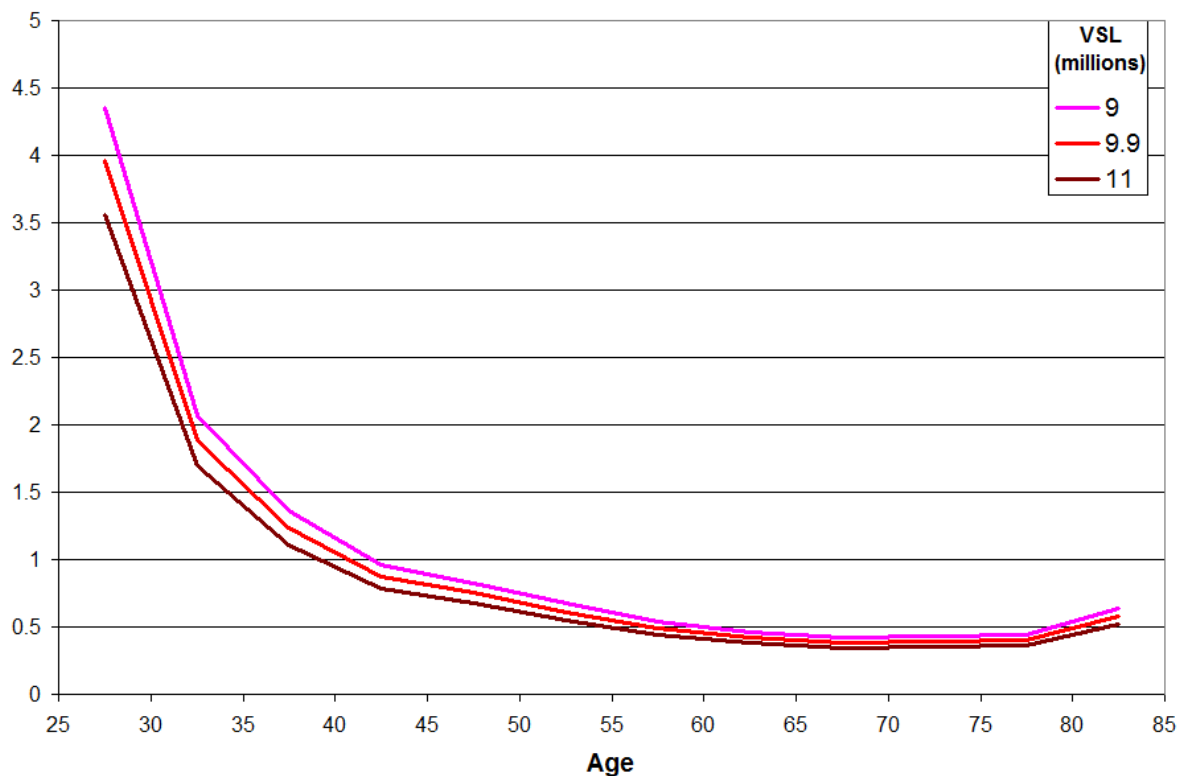
In Figure 2.13, I report results from the main quantitative exercise in the case that I choose b so that the value of statistical life for 35-44 year olds is 9 million dollars and 11 million dollars, and compare them to the baseline case in which the corresponding value is 9.9 million dollars. I scale the reported values of medical quality so that the average medical quality in the baseline case is equal to one. As shown in the figure, increases in the targeted value of statistical life lead to increases in the inferred values of medical quality for every age group. The reason for this is that, fixing the level of consumption in each period, an increase in the

Figure 2.12: Inferred Medical Quality Profile For Variation in η , Relative to Average Medical Quality for each η



targeted value of statistical life leads to an increase in the inferred value of b , and therefore an increase in the level of utility in each period. As a result, an increase in the targeted value of a statistical life leads to an increase in the marginal value of medical purchases, holding all else constant. Then, for a fixed level of medical purchases, a higher value of the value of statistical life implies that a lower level of medical quality is necessary in order for the marginal value of medical purchases to be equal to the marginal value of non-medical consumption. As seen in the picture, similar to the case of variation in η , changes in the targeted value of statistical life scale the inferred values of medical quality, and do not have a large impact on the shape of the life cycle profile of medical quality.

Figure 2.13: Inferred Medical Quality Profile For Variation in the Value of Statistical Life, Relative to Average Medical Quality in the Baseline Case



2.9 Conclusion

This paper studies the accumulation and depreciation of health capital over the life cycle. The key contribution of this paper is the development of methods to infer the quality of medical purchases in the accumulation of health capital, and the rate at which health capital depreciates over the life cycle. This is an important contribution because the quantitative analysis of policy related to the allocation of resources to medical purchases requires careful modeling of the medical decision process, and careful inference of the associated parameters. The methods developed here can be extended to study a wide variety of topics, including the change in medical quality and the depreciation rate of health capital over time, and

variation in medical quality and the depreciation rate of health capital across various demographic characteristics, including race, region, and educational attainment. These methods can also be extended to evaluate and design policy along various dimensions.

Chapter 3

A NOTE ON SHARING RULES IN TEAMS

3.1 Introduction

Consider the "Moral Hazard in Teams" game, introduced by Holmstrom (1982). It is well-known in this setting that many outcomes, including nearly all efficient ones, cannot be implemented using balanced-budget contracts, which I will call sharing rules. I show that, with standard regularity conditions on production and utility functions, all outcomes that can be implemented by a sharing rule can be implemented by a linear contract, in which all agents receive a constant share of output plus a transfer. Because of this, a compact set of implementable outcomes can be considered without loss of generality. Then, the sharing rule whose outcome maximizes welfare exists.

A large volume of work has attempted to solve the partnership problem in other settings. In particular, work has been focused on the implementation of efficient or almost-efficient outcomes in slightly different environments (see, e.g., Legros and Matsushima (1991), Legros and Matthews (1993), and Obara and Rahman (2009)). Nandeibam (2002) breaks from this literature, and attempts to characterize implementable outcomes given standard primitives and relatively smooth budget balancing contracts.

In this paper, I extend the work of Nandeibam (2002) . In that paper, he proves that all interior outcomes which can be implemented using a piecewise continuously differentiable contract can be implemented by a linear contract. Then, outcomes can be implemented by simple linear contracts, or by complex contracts which are not piecewise continuously differentiable. This set is a large, and non-compact, subset of the contract set. I extend this by considering the entire set of contracts, and proving that linear contracts can implement all implementable outcomes. This result is analogous to the Revelation Principle. Of all of the

complex possibilities for sharing rules, none can implement outcomes which are different than those of simple, linear contracts.

I am able to prove this result by characterizing the set of potential left and right-hand derivatives of contracts about all equilibria. Using this characterization and elementary methods, I prove that contracts are differentiable about all equilibrium output levels, and therefore all equilibria can be implemented by a linear contract. This result is true because the budget balance condition on contracts forces marginal utility to be zero at any interior Nash Equilibrium for all players. Any budget balancing contract must be, by definition, increasing one for one with output in the aggregate, linking the marginal utilities of the agents.

The rest of the paper is organized as follows. In section 2, I present the details of the model. In section 3, I prove the main result in the case of two agents, and I prove that the welfare-maximization problem is well-defined in section 4. I extend the main result to the n -agent case in section 5. I conclude in section 6.

3.2 Model

In this model, n agents are engaged in team production. Each agent i chooses a non-negative effort levels $a_i \in \mathbb{R}_+$, which is unobservable. Let $a = (a_1, \dots, a_n)$ denote an action profile. The action profile a determines output $f : \mathbb{R}_+^n \rightarrow \mathbb{R}_+$. A contract $p : \mathbb{R}_+ \rightarrow \mathbb{R}^n$ specifies how output is divided between agents. Individual effort is unobservable, and contracts must be contingent on total output. Individual i has preferences over consumed output and exerted effort given by the utility function $U^i : \mathbb{R} \times \mathbb{R}_+ \rightarrow \mathbb{R}$, with the first argument denoting the amount of output that the agent consumes. Following Nandeibam (2002), I consider primitives with standard regularity conditions. The production function f is continuously differentiable, strictly increasing and concave on \mathbb{R}_{++}^2 . An individual i 's utility function U^i is continuously differentiable, concave and strictly increasing in the first argument, concave and strictly decreasing in the second argument, with

$U_2^i(x, 0) = 0$ and $U_2^i(x, \infty) = \infty$. I normalize $f(0, \dots, 0) = 0$ and $U^i(0, 0) = 0$. I break from Nandeibam (2002) only in the assumption that marginal utility from good one eventually declines to zero. This assumption is necessary for the welfare maximization problem to be well-defined. Otherwise, a social planner may want to write a contract which transfers infinite consumption to one agent.

I consider all contracts p satisfying budget balance, which means for all $y \in \mathbb{R}_+$, $\sum p_i(y) = y$. Let $BB(n)$ denote the set of budget balancing contracts which divide output between n agents. Let $NE(p)$ denote the set of Nash Equilibria given contract p . An outcome (x^*, a^*) is implementable if there exists a contract p such that $a^* \in NE(p)$ and $x^* = p_i(f(a^*))$ for all i .

3.3 Main Result

I prove that all outcomes that are implementable by a budget balancing contract can be implemented by a linear contract. I do so in a few steps by characterizing contracts about a Nash Equilibrium output level. First, I prove that contracts are continuous about the equilibrium. Then, I characterize the set of left and right-hand derivatives about the equilibrium. I use this characterization to prove that all equilibria can be implemented using a linear contract. For illustrative purposes, I prove the result in the two-agent case. I extend this to the n -agent case in the next section. As a consequence of this result, the welfare maximization problem is also well-defined in this case.

To begin, I will restrict attention to Nash Equilibria in which all players choose interior actions. It is straightforward to extend the result to Nash Equilibria in which at least one player provides zero effort. I will prove this for the two-player case first. The proof for the n -player case, as I will show, is a simple extension of the proof for the two-player case. To be precise, I will prove the following: For all $p \in BB(2)$, all $a \in NE(p)$, there exists s_1 such that the linear contract

$q(y) = [s_1 y, (1 - s_1)y]$ implements $(p(a), a)$.

I begin by characterizing the contract about an equilibrium. For ease of notation, let BB denote $BB(2)$. I maintain the assumption that equilibria are interior throughout.

Lemma 1 *For all $p \in BB$ and all $a^* \in NE(p)$, $p(x)$ is continuous at $f(a^*)$*

Proof. *Let $p \in BB$ and $a^* \in NE(p)$ be given. Suppose that p is not continuous at $f(a^*)$. Then, since $p \in BB$, there exists $I > 0$ such that for all $\epsilon > 0$ there exists i and $z \in B(\epsilon, f(a^*))$ such that $p_i(z) > I + p_i(f(a^*))$. Then, since U^i and f are continuous, there exists b_i sufficiently close to a_i^* such that $U^i(p_i(f(a_{-i}^*, b_i)), b_i) > U^i(p_i(f(a^*)), a_i^*)$. Then $a^* \notin NE(p)$, contradicting hypothesis. Therefore p is continuous at $f(a^*)$. ■*

I wish to characterize the sets of left and right-hand derivatives of the payoff function about the equilibrium. To be more precise, let $R_i(a^*, p)$ be the set of limits, as $h \rightarrow 0$, of

$$\frac{U^i(p_i(f(a_i^* + |h|, a_{-i}^*)), a_i^*) - U^i(p_i(f(a^*)), a_i^*)}{|h|} \quad (3.1)$$

Let $L_i(a^*, p)$ be defined analogously for the set of left-hand derivatives of player i 's payoff function about the equilibrium. For ease of notation, I refer to these sets as R_i and L_i . Note that these sets are non-empty and bounded. In particular, $\limsup_{h \rightarrow 0} \frac{p_i(f(a_i^* + |h|, a_{-i}^*)) - p_i(f(a^*))}{|h|} \in R_i$. Since contracts satisfy budget balance, the existence of an infinitely sloped trajectory about the equilibrium would lead to a positive deviation for at least one of the players. The relevant members of these sets are those along which agents have the best possible deviations. To the right, for example, agents would like to deviate along with trajectory with the highest slope. With this in mind, let $r_i = \sup\{R_i\}$ and $l_i = \inf\{L_i\}$. For ease of notation, let $c_i'(a_i^*) = U_2^i(p_i(f(a^*)), a_i^*)$. Note that, since p is continuous at $f(a^*)$, c_i' is also

continuous at a_i^* . About an equilibrium, utility cannot be decreasing in effort to the left, or increasing in effort to the right. This allows me to characterize r_i and l_i .

Lemma 2 For all $p \in BB$, all $a^* \in NE(p)$, and all i , $r_i + c'_i(a_i^*) \leq 0$ and $l_i + c'_i(a_i^*) \geq 0$.

Proof. Let $p \in BB$, $a^* \in NE(p)$, i be given. Suppose, to the contrary, that $r_i + c'_i(a_i^*) > 0$. Then there exists $r \in R_i$ such that $r + c'_i(a_i^*) > 0$. Then, since p is continuous at a^* , there exists $x > a_i^*$ such that $U^i(p_i(f(a_{-i}^*, x)), x) > U^i(p_i(f(a^*)), a_i^*)$. Then $a^* \notin NE(p)$, contradicting the hypothesis. Therefore $r_i + c'_i(a_i^*) \leq 0$. Similarly, $l_i + c'_i(a_i^*) \geq 0$. ■

A trivial, but important, consequence of this is that $l_i \geq r_i$.

Next, I decompose the sets of derivatives into the derivative of the contract and the derivative of the production function. By the chain rule, along differentiable paths, I have $\frac{dp_i}{da_i}(f(a^*)) = p'_i(f(a^*))U_1^i(p_i(f(a^*)), a_i^*)f_i(a^*)$. Let $S_i^l = \left\{ \frac{L_i}{U_1^i(p_i(f(a^*)), a_i^*)f_i(a^*)} \right\}$ and $S_i^r = \left\{ \frac{R_i}{U_1^i(p_i(f(a^*)), a_i^*)f_i(a^*)} \right\}$, denoting the left and right-hand derivatives of the payoff function with respect to output at the equilibrium. By budget balance, $p_1(y) + p_2(y) = y$. Therefore, along differentiable paths, $p'_1(y) + p'_2(y) = 1$. Then, if $a \in S_1^l$, $1 - a \in S_2^l$. Let $s_i^l = \inf\{S_i^l\}$, and $s_i^r = \sup\{S_i^r\}$. Then $s_1^l + s_2^l = \inf\{S_1^l\} + \inf\{S_2^l\} = \inf\{S_1^l\} + 1 - \sup\{S_1^l\} \leq 1$. Similarly, $s_1^r + s_2^r \geq 1$

Lemma 3 $s_1^l + s_2^l = s_1^r + s_2^r = 1$

Proof. Suppose, to the contrary, that $s_1^l + s_2^l < 1$. By Lemma 2, $l_i \geq r_i$, then, since f is increasing, $s_i^l \geq s_i^r$. Then, $s_1^r + s_2^r \leq s_1^l + s_2^l < 1$, contradicting the fact that $s_1^r + s_2^r \geq 1$. Therefore, $s_1^l + s_2^l \geq 1$. Therefore $s_1^l + s_2^l = 1$. Similarly, $s_1^r + s_2^r = 1$. ■

Corollary 1 For each i , p_i is differentiable at $f(a^*)$, $s_i^l = s_i^r$ and

$$s_i^l f_i(a^*) + c_i'(a_i^*) = s_i^r f_i(a^*) + c_i'(a_i^*) = 0$$

Proof. $s_1^l + s_2^l = s_1^r + s_2^r$, $s_1^l \geq s_1^r$, and $s_2^l \geq s_2^r$. Then, trivially, $s_1^l = s_1^r$ and $s_2^l = s_2^r$.

Then, by Lemma 2, $s_i^l f_i(a^*) + c_i'(a_i^*) = s_i^r f_i(a^*) + c_i'(a_i^*) = 0$. By Lemma 3,

$s_1^l + s_2^l = 1$. Then $\inf\{S_i^l\} = \sup\{S_i^l\}$, implying left and right-differentiability.

Then, since, $s_i^l = s_i^r$, p_i is differentiable at $f(a^*)$. ■

This effectively characterizes the contracts, and allows us to prove that all implementable outcomes in this setting can be implemented by a linear sharing rule. Notice that, if one assumes piecewise differentiability of contracts, as in Nandeibam (2002), then proving Corollary 1 is the only step necessary in order to prove differentiability of the contracts at the equilibrium output level, completing the characterization.

Proposition 1 For all $p \in BB$, all $a^* \in NE(p)$, there exists s_1, s_2, T such that the linear contract $q(y) = [s_1 y + T, s_2 y - T]$ implements $(p(a^*), a^*)$.

Proof. Let $p \in BB$, $a^* \in NE(p)$ be given. Let $s_i = s_i^l$, and $T = p_1(f(a^*) - s_1 f(a^*))$.

By previous argument, $s_i U_1^i(p_i(f(a^*)), a_i^*) f_i(a^*) + c_i'(a_i^*) = 0$. Then, since

$U^i(q_i(f_i(a_i, a_{-i}^*)), a_i)$ is concave, a_i^* is the best response to a_{-i}^* . Therefore

$a^* \in NE(q)$. By construction, $p(a^*) = q(a^*)$. Therefore q implements $(p(a^*), a^*)$. ■

Therefore all outcomes implementable by budget balancing contracts can be implemented by linear budget balancing contracts.

As I mentioned previously, it is straightforward to show that all boundary outcomes can be implemented by a linear contract. Note that, since the marginal cost of effort is zero on the boundary, at least one player will exert positive effort in all equilibria. Consider an equilibrium of a contract p in which agent one exerts

positive effort a_1^* , and agent two exerts zero effort. Then the linear contract with $s_1 = -\frac{c_1'(a_1^*)}{f_1(a_1^*, 0)}$ and $T = p_1(f(a_1^*, 0) - s_1 f(a_1^*, 0))$ implements the outcome. By construction, agent one's first order condition holds, and $(1 - s_1) \leq r_2 \leq -c_2'(0)$, implying that it is optimal for agent two to exert zero effort.

3.4 Welfare

I am left with the problem of maximizing welfare:

$$\max_{s_1, T} \left\{ \max_{a \in NE(s_1, T)} [\alpha^1 U^1(s_1 f(a) + T, a_1) + \alpha^2 U^2((1 - s_1)f(a) - T, a_2)] \right\} \quad (3.2)$$

In order to prove that this maximization problem is well-defined, I need to show that a compact set of implementable outcomes can be considered without loss of generality. Since marginal costs converge to positive infinity and marginal utility converges to zero, the set of outcomes in which welfare is greater than zero is compact. Further, outcomes in which one player gets a negative share of output are dominated by outcomes in which that player gets no share of output. This allows us to consider a compact set of contracts without loss of generality.

Proposition 2 *The welfare maximization problem in (2) is well defined.*

Proof. *Since marginal costs converge to positive infinity and marginal utility converges to zero, the set of outcomes in which welfare is greater than zero is compact. Then there exists a \bar{T} such that $T > \bar{T}$ implies that welfare is negative. Let $s_1 > 1, T$ be given. Then there exists $(a_1, 0) \in NE(s_1, T)$. From the first order condition, marginal cost of effort is greater than marginal utility from consumption for agent one in equilibrium. This equilibrium is Pareto dominated by $(a_1^*, 0) \in NE(1, T)$, since player two's consumption has increased, and player one has chosen the optimal level of effort subject to $a_2 = 0$. Then, with respect to welfare, we need only consider contracts with $0 \leq s_1 \leq 1$ and $|T| \leq \bar{T}$. Let $(a_n, T_n)_{n=1:\infty}$ characterize a of these contracts converging to (a^*, T^*) . Then there*

exists a sequence $(s_{1,n}, T_n)_{n=1:\infty}$ such that $(a_n, T_n) \in NE(s_{1,n}, T_n)$ for all n . Then, since we consider a compact contract space, there exists a subsequence converging to (s_1^*, T^*) . Then, since the first order condition is continuous in all of the variable, it follows that $(a^*, T^*) \in NE(s_1^*, T^*)$. Then the space of outcomes implemented by these contracts is closed. Then the set of outcomes implemented by these contracts in which welfare is nonnegative is compact. Then the welfare maximization problem is well-defined. ■

3.5 n-Player Case

Until now, I have only considered the two-player case. The extension to the n -player case is straightforward. Lemmas 1 and 2 follow immediately. The extension of lemma 3 is not immediately obvious. In particular, if p_1 is differentiable along some path, $1 - p_1$ is differentiable along the same path. If there are more than two players, p_2 is not necessarily differentiable along all of the same paths as p_1 . However, there will be a path along which p_1 and p_2 will be differentiable, and so on. Therefore, for all $s \in S_n^l$, there exists a path along which all p_i 's are differentiable. I will apply this to prove the inequalities $\sum s_i^l \leq 1$ and $\sum s_i^r \geq 1$ still hold, allowing us to apply the same methodology to infer the the left and right-hand shares sum to one.

Proposition 3 $\sum s_i^l \leq 1$ and $\sum s_i^r \geq 1$

Proof. Suppose, to the contrary, that $\sum_{i=1}^n s_i^l = \alpha > 1$. Let $\epsilon = \frac{\alpha - s_1}{2}$. There exists $s_1 \in S_1^l$ with $s_1 - s_1^l < \epsilon$. Then, by budget balance, there exists $\{\tilde{s}_i^l \in S_i^l\}_{i=2}^n$ such that $s_1 + \sum_{i=2}^n \tilde{s}_i^l = 1$. Then $\sum_{i=2}^n s_i^l - \sum_{i=2}^n \tilde{s}_i^l > \alpha - 1 - \epsilon$. Then there exists \tilde{s}_j^l such that $s_j^l - \tilde{s}_j^l > \frac{\alpha - 1 - \epsilon}{n-1} > 0$. Then $s_j^l \neq \inf\{S_j^l\}$, contradicting hypothesis. Then $\sum_{i=1}^n s_i^l \leq 1$.

Similarly, $\sum_{i=1}^n s_i^r \geq 1$. ■

Using these inequalities and $s_i^r \leq s_i^l$, I have $1 \geq \sum_{i=1}^n s_i^l \geq \sum_{i=1}^n s_i^r \geq 1$, and therefore $\sum_{i=1}^n s_i^l = \sum_{i=1}^n s_i^r = 1$. The rest of the results follow immediately. Therefore, I need only consider linear contracts for the n-player case as well. Further, the problem of choosing the contract which maximizes welfare is also well-defined in the n-player case.

3.6 Conclusion

The "Moral Hazard in Teams" game has been studied extensively. In particular, there has been a large volume of work on the implementation of efficient or almost-efficient outcomes in slightly different environments. Nandeibam (2002) breaks from this literature, and attempts to characterize implementable outcomes given standard conditions on primitives and relatively smooth budget balancing contracts. I continue work along these lines by characterizing outcomes of arbitrary budget balancing contracts. I prove that all outcomes that are implementable by budget balancing contracts can be implemented by linear contracts. One important implication is that, in seeking out the optimal sharing rule, one needs only to consider the simple problem of choosing the best linear contract.

REFERENCES

- [1] Aldy, Joseph, and W. Kip Viscusi. 2008. "Adjusting the Value of a Statistical Life for Age and Cohort Effects," *The Review of Economics and Statistics*, MIT Press, vol. 90(3), pp. 573-581, 04.
- [2] Becker, Gary, Tomas Philipson, and Rodrigo Soares. 2005. "The Quantity and Quality of Life and the Evolution of World Inequality. " *American Economic Review* 95:1 pp. 277-291
- [3] Berndt, Ernst R., David M. Cutler, Richard Frank, Zvi Griliches, Joseph P. Newhouse, and Jack E. Triplett. 2001. "Price Indexes for Medical Care Goods and Services – An Overview of Measurement Issues. "in *Medical Care Output and Productivity* , ed. Cutler and Berndt, Chicago, IL: University of Chicago Press.
- [4] Cutler, David M and Mark McClellan. 2001. "Is Technological Change in Medicine Worth It?" *Health Affairs* 20, no. 5: 11–29
- [5] Di Matteo, Livio. 2005. "The Macro Determinants of Health Expenditure in the United State and Canada: Assessing the Impact of Income, Age Distribution and Time," *Health Policy* 71(1): 23-42
- [6] Duggan, Mark, and William Evans. 2005. "Estimating the Impact of Medical Innovation: A Case Study of HIV Antiretroviral Treatments," *NBER Working Paper* 11109.
- [7] Fang, H., M. Keane, A. Khwaja, M. Salm and D. Silverman. 2007. "Testing the Mechanisms of Structural Models: The Case of the Mickey Mantle Effect." *American Economic Review*, 97(2): 53-59.
- [8] Fogel, Robert. 1995. "The Contribution of Improved Nutrition to the Decline in Mortality Rates in Europe and America," in *The State of Humanity*, Simon, J. (ed.). Blackwell Publishers nc., Maldin, MA
- [9] Goldman, D., and J.P. Smith. 2005. "Socioeconomic Differences in the Adoption of New Medical Technologies. " *The American Economic Review*, 95(2):234-237.
- [10] Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health." *The Journal of Political Economy*, Vol. 80, No. 2

- [11] Hall, Robert and Charles Jones. 2007. "The Value of Life and the Rise in Health Spending." *Quarterly Journal of Economics*.
- [12] Heidenreich, Paul A. and Mark McClellan. 2001. "Trends in Treatment and Outcomes for Acute Myocardial Infarction: 1975-1995," *American Journal of Medicine* (15 February 2001): 165-174
- [13] Holliday, Robin. 1995. *Understanding Ageing*. Cambridge University Press. New York, NY.
- [14] Holmstrom, Bengt. 1982. "Moral hazard in teams," *Bell J. Econ.* 13, 324-340.
- [15] Jones, Charles. 2003. "Why Have Health Expenditures as a Share of GDP Risen So Much?" U.C. Berkeley mimeo.
- [16] Kniesner, Thomas J., W. Kip Viscusi, and James P. Ziliak, 2006. "Life-Cycle Consumption and the Age-Adjusted Value of Life," *The B.E. Journal of Economic Analysis and Policy*, Berkeley Electronic Press, vol. 0(1).
- [17] Krone, Ronald J., Rao, Sunil V., Dai, David, Anderson, H. Vernon, Peterson, Eric D., Brown, Michael A., Brindis, Ralph G., Klein, Lloyd W., Shaw, Richard E., Weintraub, William S. 2010. "Acceptance, Panic, and Partial Recovery: The Pattern of Usage of Drug-Eluting Stents After Introduction in the U.S.," *J Am Coll Cardiol Interv.* 3: 902-910
- [18] Legros, Patrick, and Hitoshi Matsushima. 1991. "Efficiency in partnerships," *J. Econ. Theory* 55, 296-322.
- [19] Legros, Patrick, and Steven Matthews. 1993. "Efficient and nearly-efficient partnerships," *Rev. Econ. Stud.* 68, 599-611.
- [20] Lichtenberg, Frank R. and Suchin Virabhak. 2002. "Pharmaceutical Embodied Technical Progress, Longevity, and Quality of Life: Drugs as 'Equipment for your Health'," *Managerial and Decision Economics*, vol. 28(4-5): 371-392
- [21] Lucarelli, Claudio and Sean Nicholson. 2009. "A Quality-Adjusted Price Index for Colorectal Cancer Drugs" <http://www.nber.org/papers/w15174.pdf>
- [22] Meara, Ellen, Chapin White and David M. Cutler. 2004. "Trends in Medical Spending by Age: 1963-2000." *Health Affairs*, 23, no. 4: 176-183

- [23] Nandeibam, Shasikanta, 2002. "Sharing Rules in Teams," J. Econ. Theory 107, 407-420.
- [24] Newhouse, Joseph. 1992. "Medical care costs: How much welfare loss?" Journal of Economic Perspectives, 6(3):3-21.
- [25] Nordhaus, William. 1997. "Traditional Productivity Estimates Are Asleep at the (Technological) Switch." The Economic Journal, 107 (September), 1548-1559.
- [26] Rahman, David, and Ichiro Obara. 2010. "Mediated Partnerships," Econometrica, 78, 285-308.
- [27] Shapiro, I., M.D. Shapiro, and D.W. Wilcox. 2001. "Measuring the Value of Cataract Surgery," in Medical Care Output and Productivity, ed. Cutler and Berndt, Chicago, IL: University of Chicago Press.
- [28] Skinner, Jonathan and Doug Staiger. 2009. "Technology Diffusion and quality Growth in Health Care." <http://www.nber.org/papers/w14865.pdf>
- [29] Viscusi, W. Kip and Joseph Aldy. 2003. "The Value of a Statistical Life: A Critical Review of Market Estimates throughout the World," Journal of Risk and Uncertainty, 27, 5-76.
- [30] Suen, Richard. 2006. "Technological Advance and the Growth in Health Care Spending." http://www.richardsuen.net/files/Tech_HCS.pdf

Appendix A

DETAILS OF ESTIMATION PROCEDURE

In this appendix, I present the details of the procedure used to estimate parameter values.

Decision Rule Computation

Decision rules are solved for computationally. At age a in period t , decision rules can be determined uniquely as a function of current period variables and the function $v_{a+1,t+1}(k)$. Since individuals die with probability one after turning age 100, it is simple to compute the value of turning 99 for each k in each time period. Using this value, we can work backwards to compute decision rules as a function of a , t , and parameter values.

In order to avoid computing $v_{a,t}(k)$ for all values of k , I take a two-step approach. First, decisions are computed taking savings decisions as given. Then, savings decisions are updated using the life cycle consumption profiles, and the optimization problem is solved again. I repeat this process until no agents wish to increase or decrease their savings. The initial level of savings for agents must also be calculated. In order to do this, savings is projected backwards linearly for all age groups at the end of each step in computing the savings decision.

Estimation Procedure

The preference parameter α , the quality parameters $A_{i,t}$ and $\gamma_{i,A}$, and the initial survival rate parameters $\psi_{a,t}$ for ages 25-84 and years 1996-2067 must be estimated. I will refer to a vector of these parameters as Θ throughout this section. Recall that preference parameter ϕ is chosen so that the value of a statistical life for 35-44 year-olds in 2000 is 9.9 million dollars. The basic strategy is to choose the remaining parameter values so that model predictions for medical expenditures and survival rates closely match the data. The main problem lies in the fact that there are a very large number of $\psi_{a,t}$ parameters to estimate. This problem is solved by converting the estimation procedure into a fixed point problem.

A mapping F from medical decision rules and survival rates into parameter vectors is constructed, and another mapping G from parameter vectors into medical decision rules and survival rates is constructed. These mappings are constructed so that any fixed point of the composed mapping $G \circ F$ corresponds to a parameter vector for which model predictions for medical decisions and survival rates closely match the data. The mapping G maps parameter vectors into model predictions for medical decision rules and survival rates. The mapping F maps decisions rules \tilde{x} and survival rates \tilde{s} into the parameter vector which maximizes the likelihood of the observed values $x_{a,t}^{data}$ and $s_{a,t}^{data}$ subject to the constraint that model predictions for survival rates at decision rule \tilde{x} are equal to \tilde{s} . This restriction allows me to search over the medical quality parameters rather than the medical quality parameters and the initial survival rate parameters. The idea is to do a series of simple searches rather than one search which is much more difficult computationally.

The mapping G from parameter vectors to medical decision rules and survival rates is straightforward. It maps the parameter vector Θ into model predictions for medical decisions $x_{a,t}^*(\Theta)$, and survival rates $s_{a,t}^*(\Theta)$ for each age in each time period. To be precise:

$$G_{a,t}(\Theta) = (x_{a,t}^*(\Theta), s_{a,t}^*(\Theta))$$

The mapping F maps medical decision rules x^1 and survival rates s to the parameter vector which maximizes the likelihood of observations subject to the constraint that model predictions for survival rates at decision rule \tilde{x} are equal to \tilde{s} . In order to evaluate the likelihood of a parameter vector given observations, $L(\Theta; x^{data}, s^{data})$, I assume that deviations from model predictions for the share of income devoted to medical expenditures and deviations from model predictions for

¹For convenience, I use this to mean the medical decision rule for all a,t

survival rates are each independent and identically distributed. Deviations from model predictions for the share of income devoted to medical expenditures and survival rates are drawn from normal distributions with mean 0 and standard deviation σ_m and σ_s , respectively. For a pair (\tilde{x}, \tilde{s}) ,

$$F(\tilde{x}, \tilde{s}) = \arg \max_{\Theta} [L(\Theta; x^{data}, s^{data})]$$

$$\text{subject to } g(\tilde{x}_{a,t}, \psi_{a,t}) = \tilde{s}_{a,t} \quad \forall a, t$$

The main appeal of this approach is that it solving for $F(\tilde{x}, \tilde{s})$ is simple computationally. Notice that, given the imposed constraint, the parameters $A_{i,t}$ and α summarize the entire parameter vector. In particular, parameter $\psi_{a,t}$ can be written as a function of $\tilde{x}_{a,t}$, $\tilde{s}_{a,t}$, and $A_{a,t}$ as follows:

$$\psi_{a,t} = \frac{\tilde{s}_{a,t}(\tilde{x}_{a,t}A_{a,t} + 1) - \tilde{x}_{a,t}A_{a,t}}{1}$$

It is straightforward to solve for $F(\tilde{x})$ numerically, since it is now a maximization problem over a manageable number of variables rather than thousands.

At a fixed point (x^*, s^*) of the composed mapping $G \circ F$, along with the corresponding parameter vector $\Theta^* = F(x^*, s^*)$, model predictions for survival rates and medical decisions are close the data, and medical decision rules are consistent with utility maximization. Solving for this fixed point, then, is a good estimation procedure in this setting.

The estimation procedure has been reduced to a fixed point problem. Now, the fixed point must be approximated. An iterative method is used to approximate the fixed point. There is a natural initial guess – the observed medical decision rule and survival rate – for the periods for which data is available, and the projection of this data for other years. Let (x_0, s_0) denote this initial guess. Starting at this initial guess, I solve for the sequence $(x_{i+1}, s_{i+1}) = G(F(x_i, s_i))$. There is no

guarantee, however, that this sequence converges. In order to guarantee that the sequence converges, F is slightly perturbed.

Recall the problem of solving for $F(\tilde{x}, \tilde{s})$, which can be written as:

$$F(\tilde{x}, \tilde{s}) = \arg \max_{\Theta} [L(\Theta; x^{data}, s^{data})]$$

subject to $g(\tilde{x}_{a,t}, \psi_{a,t}) = \tilde{s}_{a,t} \forall a, t$

where X_i is a set. In order to ensure that the sequence of decision rule, survival rate pairs (x_i, s_i) converges, I choose a sequence of constraint sets X_i in the maximization problem such that X_i converges to a singleton. I choose X_0 to be large, in the sense that likelihood is low at boundary values. I shrink the space by a factor of 2/3 around the maximizing parameter vector Θ_i^* iteratively. Since X_i converges to a singleton, (x_i, s_i) will also converge. In practice, shrinking the parameter space is unnecessary; the procedure converges with or without this perturbation of the problem.

Discussion

The fixed point approach, from a computational standpoint, is roughly equivalent to adding one parameter vector that must be searched over directly. Consider solving a minimization problem over one additional dimension. Without additional information about the structure of the problem, the additional dimension must be discretized, and the minimization problem must be solved for each grid point in the additional dimension. Computation time, then, increases linearly with the number of grid points in the additional dimension. Compare this to the iterative procedure employed to solve for the fixed point. The computation time is increasing linearly with the number of steps in the iterative process. The main advantage of the fixed point approach is that I avoid searching over the large $\psi_{a,t}$ space. I am able to estimate thousands of additional parameters at the computational cost of adding one additional parameter.

Another approach is to assume $\psi_{a,t}$ can be written as a parameterized function of age and time. One advantage of this approach is that it dramatically reduces the number of parameters that must be estimated. Despite the dramatic reduction in the number of parameters that must be estimated, this approach is more computationally intensive than the current method. This approach adds at least two additional dimensions to the parameter space that must be directly searched over, as opposed to the current method which searches for these parameters indirectly, which is roughly equivalent computationally to directly searching over one additional dimension. This approach is also likely to be less accurate because of the restriction on the set of $\psi_{a,t}$ parameters.

Appendix B

EXTENSION: HEALTH INVESTMENT

In this appendix, I detail the model that is extended to allow for health investment that is used to generate synthetic data. The goal of this exercise is to evaluate the accuracy of my methods in estimating the quality of medical purchases in an environment in which individuals invest in their health. To do so, I parameterize this model, and solve for optimal decision rules and realized survival rates. I use these statistics to estimate the quality of medical purchases.

In this model, there is a group of individuals that make decisions in two periods. Utility is written as:

$$u(c_1, m_1) + \beta g(m_1, \psi_1)[u(c_2, m_2) + \beta g(m_1, \psi_2(\psi_1, m_1))V] \quad (\text{B.1})$$

where u is the period utility function detailed in Section 2, g is the survival function, $\psi_2(\psi_1, m_1)$ is non-medical factors in period 2, and V is the value of surviving to period 3. Notice that ψ_2 is a function of medical consumption in period 1 as well as non-medical factors in period 1. I restrict this function to be in the form

$$\psi_2(\psi_1, m_1) = \gamma \psi^{exog} + (1 - \gamma)(1 - \delta)g(m_1, \psi_1) \quad (\text{B.2})$$

where ψ^{exog} is an exogenous parameter. The interpretation of this function is that an individual's initial survival rate tomorrow is determined in part as a function of today's survival rate, and in part by other factors, such as lifestyle decisions, etc. The baseline model corresponds to the case in which $\gamma = 1$. The function g is written as:

$$g(m, \psi) = \psi + (1 - \psi) \frac{m}{m + 1} \quad (\text{B.3})$$

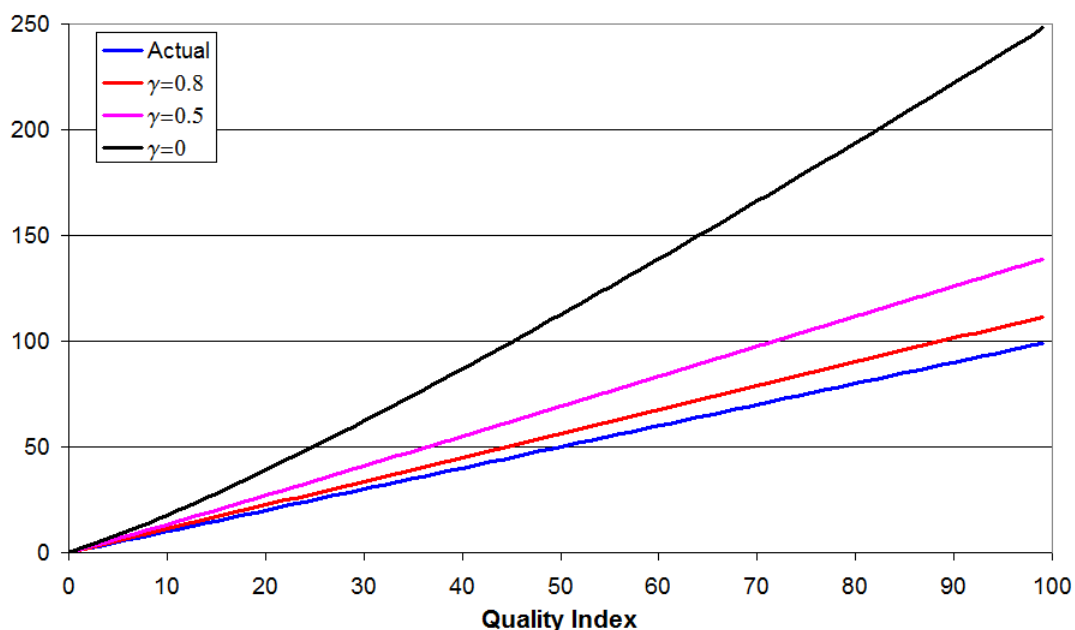
Individuals allocate income y_t to medical goods and services x_t and non-medical consumption c_t in each period t . The quality of medical goods and services is A . All prices are equal to one. Agents cannot accumulate assets, and choose allocations to maximize utility subject to their budget constraint.

I solve for optimal decision rules for a large number of parameterizations. I estimate quality using the decision rules and survival rates generated by the model

in period one. Note that, since medical consumption in period two only effects survival rates in period two, period one is the only period in which estimates of medical quality may differ from their true value. Since I am evaluating the estimation of quality, I will fix the values of all parameters unrelated to the survival function. I choose parameter values as follows: $\alpha = .993$, $V = 20$, $y = 50000$, $\psi = .99$, $\psi^{exog} = .99$, $\delta = .01$, and $\beta = .96$. Qualitatively, results are not sensitive to the choice of any of these parameter values.

I perform the estimation procedure for a wide range of values of A and γ . I choose the range of A so that all estimated values of quality reported in the paper are included in the range. I report the estimated and actual values of quality for these parameterizations in Figure B.1. For γ less than 1, estimates of quality

Figure B.1: Medical Quality, Actual and Estimated, Heterogeneity Extension



exceed actual values of quality. The extent to which estimates exceed actual values depends on the degree to which ψ_2 depends on s_1 . The smaller γ , the larger the estimation error. Abstracting from the impact of today's medical

expenditures on future survival rates can have a large impact on the estimation of medical quality. The most likely consequence of this abstraction is that estimates quality growth exceeds actual quality growth.

Appendix C

EXTENSION: HETEROGENEITY

In this appendix, I detail the model that is extended to allow for heterogeneity within age, time groups that is used to generate synthetic data. Specifically, I am interested in heterogeneity with respect to non-medical factors; some individuals are sicker than others at the start of the period. The goal of this exercise is to evaluate the accuracy of my methods in estimating the quality of medical goods and services in an environment in which individuals invest in their health. To do so, I parameterize this model. I solve for optimal decision rules and realized survival rates in period 1. I use these statistics to estimate the quality of medical goods and services.

In this model, there are two types of individuals, type 1 and type 2. Agents make decisions in one period. Utility is written as:

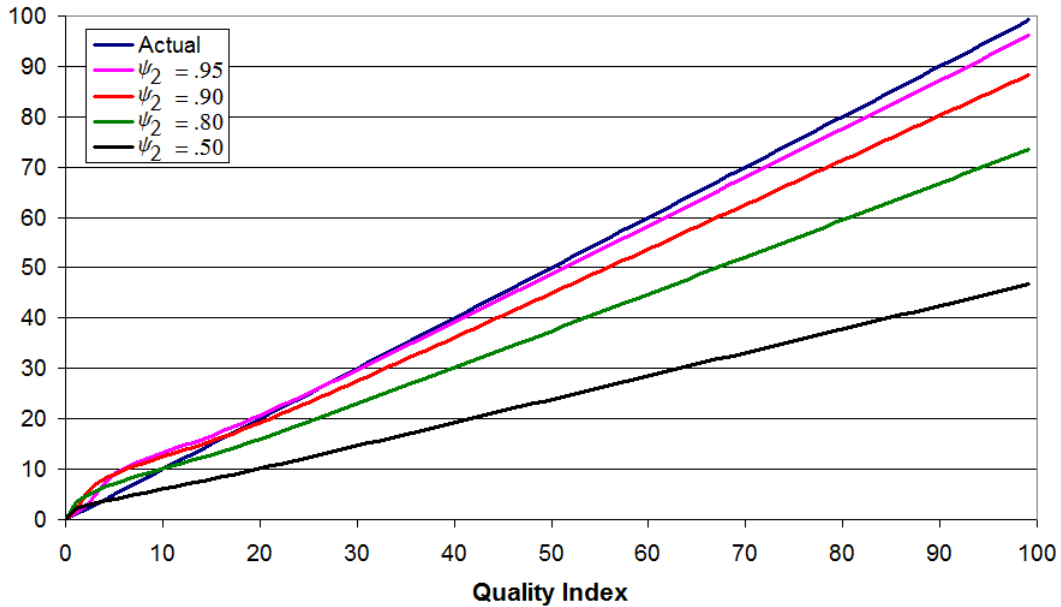
$$u(c_i, m_i) + \beta g(m_i, \psi_i)V \quad (\text{C.1})$$

where i indexes an individual's type, u is the period utility function detailed in Section 2, g is the survival function detailed earlier in this section, and V is the value of surviving to period 2. The mass of individuals of type i is ω_i . Individuals allocate income y to medical goods and services x_i and non-medical consumption c_i . The quality of medical goods and services is A . All prices are equal to one. Agents choose allocations to maximize utility subject to their budget constraint.

I solve for optimal decision rules for a large number of parameterizations. I estimate quality using the decision rules and survival rates generated by the model. Since I am evaluating the estimation of quality, I assume that I already know the values of all parameters unrelated to the survival function. I use the following parameter values: $\alpha = .993$, $V = 20$, $y = 50000$, $\psi_1 = .99$, $\omega_1 = .8$, $\omega_2 = .2$, and $\beta = .96$. Qualitatively, results are not sensitive to the choice of any of these parameter values. I perform the estimation procedure for a wide range of values of A and ψ_2 . I choose the range of A so that all estimated values of quality

reported in the paper are included in the range. I report the actual value and the estimated value of medical quality for a variety of values of ψ and A in Figure C.1.

Figure C.1: Medical Quality, Actual and Estimated, Health Investment Extension



In general, estimates of quality fall below actual values of quality. This is not the case for particularly low values of A , for which estimates of quality substantially exceed their actual values. For most values of A , the larger the degree of heterogeneity in the population, the larger the degree to which actual values of medical quality exceed estimates of medical quality. Since I focus on the growth rate of quality, one particular concern is that quality is in the range in which estimated quality growth is much faster than actual quality growth. The most likely consequence of abstracting from within-cohort heterogeneity in ψ is that I am overestimating the growth rate of quality. Similar parameterizations yield similar results.