

The Value of Life and the Rise in Health Spending

Robert E. Hall

Hoover Institution and Department of Economics, Stanford University and NBER

E-mail: rehall@stanford.edu

<http://stanford.edu/~rehall>

and

Charles I. Jones*

Department of Economics, U.C. Berkeley and NBER

E-mail: chad@econ.berkeley.edu

<http://elsa.berkeley.edu/~chad>

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Health care extends life. Over the past half century, Americans spent a rising share of total economic resources on health and enjoyed substantially longer lives as a result. Debate on health policy often focuses on limiting the growth of health spending. We investigate an issue central to this debate: Is the growth of health spending the rational response to changing economic conditions—notably the growth of income per person? We develop a model based on standard economic assumptions and argue that this is indeed the case. Standard preferences—of the kind used widely in economics to study consumption, asset pricing, and labor supply—imply that health spending is a superior good with an income elasticity well above one. As people get richer and consumption rises, the marginal utility of consumption falls rapidly. Spending on health to extend life allows individuals to purchase additional periods of utility. The marginal utility of life extension does not decline. As a result, the optimal composition of total spending shifts toward health, and the health share grows along with income. This effect exists despite sharp diminishing returns in the technology of life extension. In projections based on the quantitative analysis of our model, the optimal health share of spending seems likely to exceed 30 percent by the middle of the century.

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1. INTRODUCTION

The United States devotes a rising share of its total resources to health care. The share was 5.2 percent in 1950, 9.4 percent in 1975, and 15.4 percent in 2000. Over the same period, health has improved. The life expectancy of an American born in 1950 was 68.2 years, of one born in 1975, 72.6 years, and of one born in 2000, 76.9 years.

Why has this health share been rising, and what is the likely time path of the health share for the rest of the century? We present a framework for answering these questions. In the model, the key decision is the division of total resources between health care and non-health consumption. Utility depends on quantity of life—life expectancy—and quality of life—consumption. People value health spending because it allows them to live longer and to enjoy better lives. In our analysis, the rise in the health share occurs because health is a superior good with an income elasticity well above one. Income growth leads consumption and health spending to rise, and the marginal utilities of both consumption and health spending to fall. But saturation occurs faster in consumption than in health spending. As people grow richer, consumption rises but they devote an increasing share of resources to health care.

In our approach, standard preferences—of the kind economists use to study issues ranging from consumption to asset pricing to labor supply—are able to explain the rising share of health spending. As consumption increases, the marginal utility of consumption falls quickly. In contrast, extending life does not run into the same kind of diminishing returns. Living an additional year allows a person to enjoy the same new flow of utility as from previous extensions of lifetime.

Many of the important questions related to health involve the institutional arrangements that govern its financing—especially Medicare and employer-

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provided health insurance. One approach would be to introduce these institutions into our model and to examine the allocation of resources that results. We take an alternative approach. We examine the allocation of resources that maximizes social welfare in our model. We abstract from the complicated institutions that shape spending in the United States and ask a more basic question: from a social welfare standpoint, how much should the nation spend on health care, and what is the time path of optimal health spending? We look at these issues from two points of view, first under the hypothesis that historical levels of health care were optimal and second under the hypothesis that they were not. In the second case, we make progress by drawing on the results of a large body of existing research on the value of a statistical life.

The recent health literature has emphasized the importance of technological change as an explanation for the rising health share—for example, see Newhouse (1992). According to this explanation, the invention of new and expensive medical technologies causes health spending to rise over time. Although the development of new technologies unquestionably plays a role in the rise of health spending, the technological explanation is incomplete for at least two reasons.

First, expensive health technologies do not need to be used just because they are invented. Although distortions in health insurance in the United States might result in over-use of expensive new technologies, health shares of GDP have risen in virtually every advanced country in the world, despite wide variation in systems for allocating health care (Jones 2003). We investigate whether the social payoff associated with the use of new technologies is in line with the cost. Second, the invention of the new technologies is itself endogenous: Why is the U.S. investing so much in order to invent these expensive technologies? By focusing explicitly on the social value of extending life and how this value changes over time, we shed light on these questions.

We begin by documenting the facts about aggregate health spending and life expectancy, the two key variables in our model. We then present a simple stylized model that makes some strong assumptions but that delivers our basic results. From this foundation, we consider a richer and more realistic framework and develop a full dynamic model of health spending. The remainder of the paper estimates the parameters of the model and discusses a number of projections of future health spending derived from the model.

Our approach is closest in spirit to the theoretical papers of Grossman (1972) and Ehrlich and Chuma (1990), who consider the optimal choice of consumption and health spending in the presence of a quality-quantity tradeoff. Our work is also related to a large literature on the value of life and the willingness of people to pay to reduce mortality risk. Classic references include Schelling (1968) and Usher (1973). Arthur (1981), Shepard and Zeckhauser (1984), Murphy and Topel (2003), and Ehrlich and Yin (2004) are more recent examples that include simulations of the willingness to pay to reduce mortality risk and calculations of the value of life. Nordhaus (2003) and Becker, Philipson and Soares (2005) conclude that increases in longevity have been roughly as important to welfare as increases in non-health consumption, both for the United States and for the world as a whole.

We build on this literature in two ways. First and foremost, the focus of our paper is on understanding the determinants of the aggregate health share. The existing literature focuses on individual-level spending and willingness to pay to reduce mortality. Second, we consider a broader class of preferences for longevity and consumption. Many earlier papers specialize for their numerical results to constant relative risk aversion utility, with an elasticity of marginal utility that is between zero and one. In part, this restriction occurs because these papers do not consider a constant term in flow utility. As we show below, careful attention to the constant is crucial to understanding the rising health share. In particular, when a constant is included, standard utility

functions that exhibit a rapidly declining marginal utility of consumption are admissible. This is the key to the rising health share in the model.

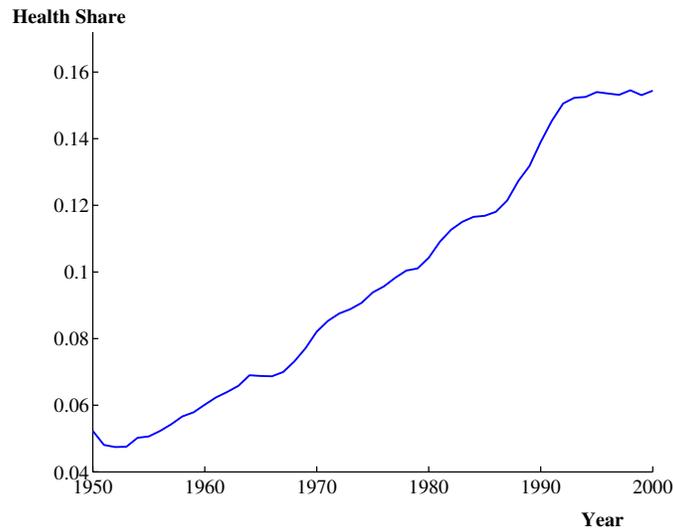
2. BASIC FACTS

We will be concerned with the allocation of total resources to health and other uses. We believe that the most appropriate measure of total resources is consumption plus government purchases of goods and services. That is, we treat investment and net imports as intermediate products. Similarly, we measure spending on health as the delivery of health services to the public and do not include investment in medical facilities. Thus we differ conceptually (but hardly at all quantitatively) from other measures that include investment in both the numerator and denominator. When we speak of consumption of goods and services, we include government purchases of non-health goods and services.

Figure 1 shows the fraction of total spending devoted to health care, according to the U.S. National Income and Product Accounts. The numerator is consumption of health services plus government purchases of health services and the denominator is consumption plus total government purchases of goods and services. The fraction has a sharp upward trend, but growth is irregular. In particular, the fraction grew rapidly in the early 1990s, flattened in the late 1990s, and resumed growth after 2000.

Figure 2 shows life expectancy at birth for the United States. Following the tradition in demography, this life expectancy measure is not expected remaining years of life (which depends on unknown future mortality rates), but is life expectancy for a hypothetical individual who faces the cross-section of mortality rates from a given year. Life expectancy has grown about 1.7 years per decade. It shows no sign of slowing over the 50 years reported in the figure. In the first half of the 20th century, however, life expectancy grew at about twice this rate, so a longer times series would show some curvature.

FIGURE 1. The Health Share in the United States



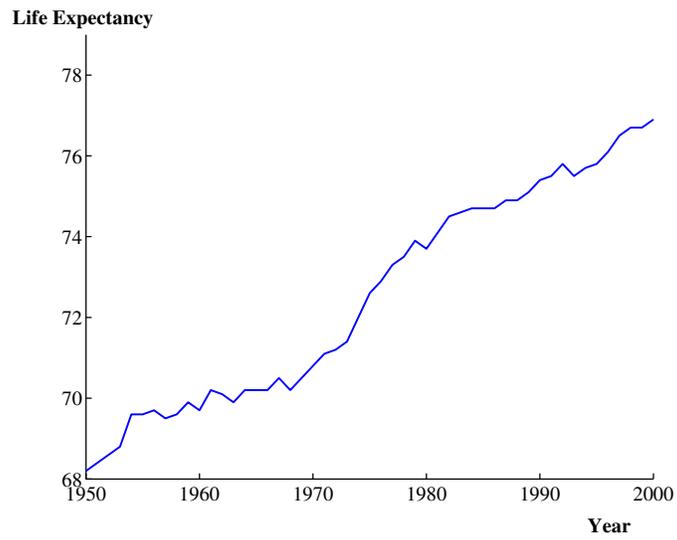
Note: The numerator of the health share is consumption of health services plus government purchases of health services and the denominator is consumption plus total government purchases of goods and services. For further information on sources, see Section 5.

3. BASIC MODEL

We begin with a model based on the simple but unrealistic assumption that mortality is the same in all age groups. We also assume that preferences are unchanging over time, and income and productivity are constant. This model sets the stage for our full model where we incorporate age-specific mortality and productivity growth. As we will show in Section 4, the stark assumptions we make in this section lead the full dynamic model to collapse to the simple static problem considered here.

The economy consists of a collection of people of different ages who are otherwise identical, allowing us to focus on a representative person. Let x denote the person's state of health, which we will call *health status*. The mortality rate of an individual is the inverse of her health status, $1/x$. Since people

FIGURE 2. Life Expectancy in the United States



Note: Life expectancy at birth data are from Table 12 of National Vital Statistics Report Volume 51, Number 3 "United States Life Tables, 2000", December 19, 2002. Center for Disease Control.

of all ages face this same mortality rate, x is also equal to life expectancy. For simplicity at this stage, we assume zero time preference.

Expected lifetime utility for the representative individual is

$$U(c, x) = \int_0^{\infty} e^{-(1/x)t} u(c) dt = xu(c). \quad (1)$$

That is, lifetime utility is the present value of her per-period utility $u(c)$ discounted for mortality at rate $1/x$. In this stationary environment, consumption is constant so that expected utility is the number of years an individual expects to live multiplied by per-period utility. We assume for now that period utility depends only on consumption; in the next section, we will introduce a quality-of-life term associated with health. Here and throughout the paper, we normalize utility after death at zero.

Rosen (1988) pointed out the following important implication of a specification of utility involving life expectancy: When lifetime utility is per-period utility, u , multiplied by life expectancy, the level of u matters a great deal. In many other settings, adding a constant to u has no effect on consumer choice. Here, adding a constant raises the value the consumer places on longevity relative to consumption of goods. Negative utility also creates an anomaly—indifference curves have the wrong curvature and the first-order conditions do not maximize utility. As long as u is positive, preferences are well behaved.¹

The representative individual receives a constant flow of resources y that can be spent on consumption or health:

$$c + h = y. \quad (2)$$

¹Rosen also discussed the following issue: If the elasticity of utility rises above one for low values of consumption—as it can for the preferences we estimate in this paper—mortality becomes a good rather than a bad. A consumer would achieve a higher expected utility by accepting higher mortality and the correspondingly higher level of later consumption. Thus one cannot take expected utility for a given mortality rate as an indicator of the welfare of an individual who can choose a lower rate. This issue does not arise in our work, because we consider explicit optimization over the mortality rate. An opportunity for improvement of the type Rosen identified would mean that we had not maximized expected utility.

The economy has no physical capital or foreign trade that permits shifting resources from one period to another.

Finally, a health production function governs the individual's state of health:

$$x = f(h). \quad (3)$$

The social planner chooses consumption and health spending to maximize the utility of the individual in (1) subject to the resource constraint (2) and the production function for health status (3). That is, the optimal allocation solves

$$\max_{c,h} f(h)u(c) \quad s.t. \quad c + h = y. \quad (4)$$

The optimal allocation equates the ratio of health spending to consumption to the ratio of the elasticities of the health production function and the flow utility function. With $s \equiv h/y$, the optimum is

$$\frac{s^*}{1 - s^*} = \frac{h^*}{c^*} = \frac{\eta_h}{\eta_c}, \quad (5)$$

where $\eta_h \equiv f'(h)\frac{h}{x}$, and $\eta_c \equiv u'(c)\frac{c}{u}$.

Now suppose we ignore the fact that income and life expectancy are taken as constant in this static model and instead consider what happens if income grows. The short-cut of using a static model to answer a dynamic question anticipates the findings of our full dynamic model quite well.

The response of the health share to rising income depends on the movements of the two elasticities in equation (5). The crux of our argument is that the consumption elasticity falls relative to the health elasticity as income rises, causing the health share to rise. Health is a superior good because satiation occurs more rapidly in non-health consumption.

Why is η_c decreasing in consumption? In most branches of applied economics, only marginal utility matters. For questions of life and death, however, this is not the case. We have normalized the utility associated with death

at zero in our framework, and how much a person will pay to live an extra year hinges on the level of utility associated with life. In our application, adding a constant to the flow of utility $u(c)$ has a material effect—it permits the elasticity of utility to vary with consumption.

Thus our approach is to take the standard constant-elastic specification for marginal utility but to add a constant to the level of utility. In this way, we stay close to the approach of many branches of applied economics that make good use of a utility function with constant elasticity for marginal utility. In finance, it has constant relative risk aversion. In dynamic macroeconomics, it has constant elasticity of intertemporal substitution. In the economics of the household, it has constant elasticity of substitution between pairs of goods.

What matters for the choice of health spending, however, is not just the elasticity of marginal utility, but also the elasticity of the flow utility function itself. With the constant term added to a utility function with constant-elastic marginal utility, the utility elasticity declines with consumption for conventional parameter values. The resulting specification is then capable of explaining the rising share of health spending.

We specify flow utility as:

$$u(c) = b + \frac{c^{1-\gamma}}{1-\gamma}. \quad (6)$$

Based on evidence discussed later in the paper, we consider $\gamma > 1$ to be likely. In this case, the base level of utility, b , needs to be positive and large enough to ensure that flow utility is always positive. The flow of utility $u(c)$ is then bounded because the exponent on consumption is negative. This means the elasticity η_c is decreasing in consumption. More generally, any bounded utility function $u(c)$ will deliver a declining elasticity, at least eventually, as will the unbounded $u(c) = \alpha + \beta \log c$. Thus the key to our explanation of the rising health share — a marginal utility of consumption that falls sufficiently

quickly — is obtained by adding a constant to a standard class of utility functions.

An alternative interpretation of the first-order condition is also informative. Let $L(c, x) \equiv U(c, x)/u'(c)$ denote the value of a life in units of output. Then, the optimal allocation of resources can also be characterized as

$$s^* = \eta_h \cdot \frac{L(c^*, x^*)/x^*}{y}. \quad (7)$$

The optimal health share is proportional to the value of a year of life L/x divided by per-capita income. If the flow of utility is given as in equation (6), it is straightforward to show that the value of a year of life satisfies

$$\frac{L(c, x)}{x} = bc^\gamma - \frac{c}{\gamma - 1}. \quad (8)$$

For $\gamma > 1$, the growth rate of the value of a life year approaches γ times the growth rate of consumption from above. Therefore, the value of a year of life will grow faster than consumption (and income) if γ is larger than 1. According to equation (7), this is one of the key ingredients needed for the model to generate a rising health share.

A rapidly-declining marginal utility of consumption leads to a rising health share provided the health production elasticity η_h does not itself fall too rapidly. For example, if the marginal product of health spending in extending life were to fall to zero — say it was technologically impossible to live beyond the age of 100 — then health spending would cease to rise at that point. As we discuss later, for the kind of health production functions that match the data, the production elasticity declines very gradually, and the declining marginal utility of consumption does indeed dominate, producing a rising health share.

Finally, we can also generalize the utility function to $U(c, x)$ in place of $xu(c)$, so that lifetime satisfaction is not necessarily proportional to the length of the lifetime. The solution for this case is $s^*/(1 - s^*) = \eta_h \eta_x / \eta_c$, where $\eta_x \equiv U_x x / U$ is the elasticity of utility with respect to life expectancy. Our

result, then, is that the health share rises when the consumption elasticity falls faster than the product of the production and life expectancy elasticities. As just one example $U(c, x) = x^\alpha u(c)$ delivers a constant η_x even with sharply diminishing returns to life expectancy (that is, α close to zero), so our main results are unchanged in this case.

The simple model develops intuition, but it falls short on a number of dimensions. Most importantly, the model assumes constant total resources and constant health productivity. This means it is inappropriate to use this model to study how a growing income leads to a rising health share, the comparative static results notwithstanding. Still, the basic intuition for a rising health share emerges clearly. The health share rises over time as income grows if the joy associated with living an extra year does not diminish as quickly as the marginal utility of consumption.

4. THE FULL DYNAMIC MODEL

We turn now to the full dynamic model, allowing age-specific mortality and the associated heterogeneity, as well as growth in total resources and productivity growth in the health sector. This model also incorporates a quality-of-life component associated with health spending.

An individual of age a in period t has an age-specific state of health, $x_{a,t}$. As in the basic model, the mortality rate for an individual is the inverse of her health status. Therefore, $1 - 1/x_{a,t}$ is the per-period survival probability of an individual with health $x_{a,t}$.

An individual's state of health is produced by spending on health $h_{a,t}$:

$$x_{a,t} = f(h_{a,t}; a, t). \quad (9)$$

In this production function, health status depends on both age and time. Forces outside the model that vary with age and time may also influence health status; examples include technological change and education.

The starting point for our specification of preferences is the flow utility of the individual, $u_{a,t}(c_{a,t}, x_{a,t})$. In addition to depending on consumption, flow utility depends on health status, $x_{a,t}$. Spending on health therefore affects utility in two ways, by increasing the quantity of life through a mortality reduction and by increasing the quality of life.

For reasons that will become clear in the empirical section, we also allow flow utility to depend on both time and age. For simplicity, we assume the time and age effects are additive, so that

$$u_{a,t}(c_{a,t}, x_{a,t}) = b_{a,t} + u(c_{a,t}, x_{a,t}) \quad (10)$$

Here $b_{a,t}$ is the base value of flow utility for a person of age a and $u(c_{a,t}, x_{a,t})$ is the part that varies with the current consumption and health status. Furthermore, we assume the invariant part of the utility function takes the following form:

$$u(c_{a,t}, x_{a,t}) = \frac{c_{a,t}^{1-\gamma}}{1-\gamma} + \alpha \frac{x_{a,t}^{1-\sigma}}{1-\sigma}, \quad (11)$$

where γ , α , and σ are all positive. The first part of this function is the standard constant-elastic specification for consumption. We assume further that health status and consumption are additively separable in utility and that quality of life is a constant-elasticity function of health status.

In this environment, we consider the allocation of resources that would be chosen by a social planner who places equal weights on each person alive at a point in time and who discounts future flows of utility at rate β . Let $N_{a,t}$ denote the number of people of age a alive at time t . Then social welfare is

$$\sum_{t=0}^{\infty} \sum_{a=0}^{\infty} N_{a,t} \beta^t u_{a,t}(c_{a,t}, x_{a,t}). \quad (12)$$

The optimal allocation of resources is a choice of consumption and health spending at each age that maximizes social welfare subject to the production

function for health in (9) and subject to a resource constraint we will specify momentarily.

It is convenient to express this problem in the form of a Bellman equation. Let $V_t(N_t)$ denote the social planner's value function when the age distribution of the population is the vector $N_t \equiv (N_{1,t}, N_{2,t}, \dots, N_{a,t}, \dots)$. Then the Bellman equation for the planner's problem is

$$V_t(N_t) = \max_{\{h_{a,t}, c_{a,t}\}} \sum_{a=0}^{\infty} N_{a,t} u_{a,t}(c_{a,t}, x_{a,t}) + \beta V_{t+1}(N_{t+1}) \quad (13)$$

subject to

$$\sum_{a=0}^{\infty} N_{a,t} (y_t - c_{a,t} - h_{a,t}) = 0, \quad (14)$$

$$N_{a+1,t+1} = \left(1 - \frac{1}{x_{a,t}}\right) N_{a,t}, \quad (15)$$

$$N_{0,t} = N_0, \quad (16)$$

$$x_{a,t} = f(h_{a,t}; a, t). \quad (17)$$

$$y_{t+1} = e^{g_y} y_t, \quad (18)$$

The first constraint is the economy-wide resource constraint. Note that we assume that people of all ages contribute the same flow of resources, y_t . The second is the law of motion for the population. We assume a large enough population so that the number of people aged $a + 1$ next period can be taken equal to the number aged a today multiplied by the survival probability. The third constraint specifies that births are exogenous and constant at N_0 . The final two constraints are the production function for health and the law of motion for resources, which grow exogenously at rate g_y .

Let λ_t denote the Lagrange multiplier on the resource constraint. The optimal allocation satisfies the following first order conditions for all a :

$$u_c(c_{a,t}, x_{a,t}) = \lambda_t, \quad (19)$$

$$\beta \frac{\partial V_{t+1}}{\partial N_{a+1,t+1}} \cdot \frac{f'(h_{a,t})}{x_{a,t}^2} + u_x(c_{a,t}, x_{a,t}) f'(h_{a,t}) = \lambda_t, \quad (20)$$

where we use $f'(h_{a,t})$ to represent $\partial f(h_{a,t}; a, t) / \partial h_{a,t}$. That is, the marginal utility of consumption and the marginal utility of health spending are equated across people and to each other at all times. This condition together with the additive separability of flow utility implies that people of all ages have the same consumption c_t at each point in time, but they have different health expenditures $h_{a,t}$ depending on age.

Let $v_{a,t} \equiv \frac{\partial V_t}{\partial N_{a,t}}$ denote the change in social welfare associated with having an additional person of age a alive. That is, $v_{a,t}$ is the social value of life at age a in units of utility. Combining the two first-order conditions, we get:

$$\frac{\beta v_{a+1,t+1}}{u_c} + \frac{u_x x_{a,t}^2}{u_c} = \frac{x_{a,t}^2}{f'(h_{a,t})}, \quad (21)$$

The optimal allocation sets health spending at each age to equate the marginal benefit of saving a life to its marginal cost. The marginal benefit is the sum of two terms. The first is the social value of life $\beta v_{a+1,t+1} / u_c$. The second is the additional quality of life enjoyed by people as a result of the increase in health status.

The marginal cost of saving a life is dh/dm , where dh is the increase in resources devoted to health care and dm is the reduction in the mortality rate. For example, if reducing the mortality rate by .001 costs \$2000, then saving a statistical life requires $1/.001 = 1000$ people to undertake this change, at a total cost of \$2 million. Our model contains health status x as an intermediate variable, so it is useful to write the marginal cost as $\frac{dh}{dm} = \frac{dh/dx}{dm/dx}$. Since health status is defined as inverse mortality, $m = 1/x$ so that $dm = dx/x^2$. In the previous example, we required $1/dm$ people to reduce their mortality rate by dm to save a life. Equivalently, setting $dx = 1$, we require x^2 people to increase their health status by one unit in order to save a statistical life. Since

the cost of increasing x is $dh/dx = 1/f'(h)$, the marginal cost of saving a life is therefore $x^2/f'(h)$.

By taking the derivative of the value function, we find that the social value of life satisfies the recursive equation:

$$v_{a,t} = u_{a,t}(c_t, x_{a,t}) + \beta \left(1 - \frac{1}{x_{a,t}}\right) v_{a+1,t+1} + \lambda_t(y_t - c_t - h_{a,t}). \quad (22)$$

The additional social welfare associated with having an extra person alive at age a is the sum of three terms. The first is the level of flow utility enjoyed by that person. The second is the expected social welfare associated with having a person of age $a + 1$ alive next period, where the expectation employs the survival probability $1 - 1/x_{a,t}$. Finally, the last term is the net social resource contribution from a person of age a , her production less her consumption and health spending.

The literature on competing risks of mortality suggests that a decline in mortality from one cause may increase the optimal level of spending on other causes, as discussed by Dow, Philipson and Sala-i-Martin (1999). This property holds in our model as well. Declines in future mortality will increase the value of life, $v_{a,t}$, raising the marginal benefit of health spending at age a .

4.1. Relation to the Static Model

It is worth pausing for a moment to relate this full dynamic model to the simple static framework. With constant income y , a time- and age-invariant health production function $f(h)$, $\beta = 1$, and a flow utility function that depends only on consumption, the Bellman equation for a representative agent can be written as

$$V(y) = \max_{c,h} u(c) + (1 - 1/f(h))V(y) \quad \text{s.t.} \quad c + h = y. \quad (23)$$

Given the stationarity of this environment, it is straightforward to see that the value function is

$$V(y) = \max_{c,h} f(h)u(c) \text{ s.t. } c + h = y, \quad (24)$$

the static model we developed earlier, restated in discrete time.

5. QUANTITATIVE ANALYSIS

In the remainder of the paper, we estimate the parameters of our model and provide a quantitative analysis of its predictions. We are conscious of uncertainty in the literature regarding the values of many of the parameters in our model. The calculations that follow should be viewed as illustrative and suggestive, and we have done our best to indicate the range of outcomes one would obtain with other plausible values of the parameters. We begin by describing the data we use, then proceed to estimating the parameter values, and finally conclude with solving the model.

We assume a period in the model is five years in the data. We organize the data into 20 five-year age groups, starting at 0–4 and ending at 95–99. We consider 11 time periods in the historical period, running from 1950 through 2000.

We obtained data on age-specific mortality rates from Table 35 of National Vital Statistics Report Volume 51, Number 3 *United States Life Tables, 2000*, December 19, 2002, Center for Disease Control. This source reports mortality rates every 10 years, with age breakdowns generally in 10-year intervals. We interpolated by time and age groups to produce estimates for 5-year time intervals and age categories. We also obtained data on age-specific mortality rates due to accidents and homicides from *Health, United States 2004* and from various issues of *Vital Statistics of the United States*.

Data on age-specific health spending is taken from Meara, White and Cutler (2004). These data are for 1963, 1970, 1977, 1987, 1996, and 2000. Using

the age breakdowns for these years, we distributed national totals for health spending across age categories, interpolated to our 5-year time intervals.

National totals for health spending are from Table 2.5.5 of the revised National Income and Product Accounts of the Bureau of Economic Analysis, accessed at bea.gov on February 13, 2004 (for private spending) and Table 3.15 of the previous NIPAs, accessed December 2, 2003 (for government spending). Data on government purchases of health services are no longer reported in the accounts. The empirical counterpart for our measure, y , of total resources is total private consumption plus total government purchases of goods and services, from the sources described above.

6. ESTIMATING THE HEALTH PRODUCTION FUNCTION

We begin by assuming a functional form for the production function for health status. Our main approach treats mortality from accidents and homicides as exogenous and assumes health inputs affect non-accident mortality. The distinction between the two categories is especially important for older children and young adults, where health-related mortality is so low that declines in accidents account for a substantial part of the overall trend in mortality. We assume that the inverse of the non-accident mortality rate — $\tilde{x}_{a,t} \equiv 1/m_{a,t}^{non}$ — is a Cobb-Douglas function of health inputs:

$$\tilde{x}_{a,t} = A_a (z_t h_{a,t} w_{a,t})^{\theta_a} . \quad (25)$$

In this production function, A_a and θ_a are parameters that are allowed to depend on age. z_t is the efficiency of a unit of output devoted to health care, taken as an exogenous trend; it is the additional improvement in the productivity of health care on top of the general trend in the productivity of goods production. The unobserved variable $w_{a,t}$ captures the effect of all other determinants of mortality, including education and pollution.

The production function for overall health is therefore:

$$x_{a,t} = f_{a,t}(h_{a,t}) = \frac{1}{m_{a,t}^{acc} + m_{a,t}^{non}} = \frac{1}{m_{a,t}^{acc} + 1/\tilde{x}_{a,t}}, \quad (26)$$

where m^{acc} is the exogenous mortality rate from accidents and homicides.

6.1. Identification

To explain our approach to identifying the parameters of this production function— A_a and θ_a — we introduce a new variable, $s_{a,t} \equiv h_{a,t}/y_t$, the ratio of age-specific health spending to income per capita. We rewrite our health production function as

$$\tilde{x}_{a,t} = A_a(z_t y_t \cdot s_{a,t} \cdot w_{a,t})^{\theta_a}. \quad (27)$$

The overall trend decline in age-specific mortality between 1950 and 2000 can then be decomposed into the three terms in parentheses. First is a trend due to technological change, $z_t y_t$. In our benchmark scenario, we assume technical change in the health sector occurs at the same rate as in the rest of the economy, so that $z_t = 1$ is constant. Because y_t rises in our data at 2.31 percent per year, this is the rate of technical change assumed to apply in the health sector. In a robustness check, we assume technical change is faster in the health sector, allowing z_t to grow at one percent per year so that technical change in the health sector is 3.31 percent.

The second cause of a trend decline in age-specific mortality is resource allocation: as the economy allocates an increasing share of per capita income to health spending at age a , mortality declines. This effect is captured by $s_{a,t}$.

Third, unobserved movements of $w_{a,t}$ cause age-specific mortality to decline. We have already removed accidents and homicides from our mortality measure, but increases in the education of the population, declines in pollution, and declines in smoking may all contribute to declines in mortality.

The key assumption that allows us to identify θ_a econometrically is that our observed trends — technological change and resource allocation — account

for a known fraction μ of the trend decline in age-specific mortality. For example, in our benchmark case, we assume that technical change and the increased allocation of resources to health together account for $\mu = 2/3$ of the decline in non-accident mortality, leaving $1/3$ to be explained by other factors. As a robustness check, we also consider the case where these percentages are 50-50, so that $\mu = 1/2$. We first discuss why this is a plausible identifying assumption and then explain exactly how it allows us to estimate θ_a .

A large body of research seeks to understand the causes of declines in mortality. Newhouse and Friedlander (1980) is one of the early cross-sectional studies documenting a low correlation between medical resources and health outcomes. Subsequent work designed to solve the difficult identification problem (more resources are needed where people are sicker) have generally supported this finding (Newhouse 1993, McClellan, McNeil and Newhouse 1994, Skinner, Fisher and Wennberg 2001, Card, Dobkin and Maestas 2004, Finkelstein and McKnight 2005). This work often refers to “flat of the curve” medicine and emphasizes the low marginal benefit of additional spending. On the other hand, even this literature emphasizes that certain kinds of spending — for example the “effective care” category of Wennberg, Fisher and Skinner (2002) that includes flu vaccines, screening for breast and colon cancer, and drug treatments for heart attack victims — can have important effects on health. Goldman and Cook (1984) attribute 40 percent of the decline in mortality from heart disease between 1968 and 1976 to specific medical treatments; Heidenreich and McClellan (2001) take this one step further and conclude that the main reason for the decline in early mortality from heart attacks during the last 20 years is the increased use of medical treatments. Of course, a substantial part of “medical treatments” may include improvements in technology (Cutler, McClellan, Newhouse and Remler 1998). Skinner et al. (2001) emphasize that technological advances have been responsible for “large average health benefits” in the U.S. population. Nevertheless, other

factors including behavioral changes, increased education, and declines in pollution have certainly contributed to the decline in mortality (Chay and Greenstone 2003, Grossman 2005).

While it would be a stretch to say there is a consensus, this literature is generally consistent with the identifying assumption made here. In particular, our identifying assumption leads to the following decomposition of the sources of age-specific mortality decline. Averaged across our age groups, 35 percent is due to technological change, 32 percent to increased resource allocation to health, and 33 percent (by assumption) to other factors. In our robustness check that assigns 50 percent to other factors, the split is 26 percent to technological change and 24 percent to increased resource allocation. When we allow technical change to be a percentage point faster in the health sector, 40 percent of the mortality decline is due to technical change, 27 percent to resource allocation, and 33 percent (by assumption) to unobserved factors.

Our assumption about the fraction μ implies that there is a trend in the unobservable $w_{a,t}$ that accounts for a fraction $1 - \mu$ of the improvement in mortality in age group a . The ratio of the trend in the unobserved component to the trend in the observed component based on technical change and rising resources is $\frac{1-\mu}{\mu}$. The remaining part of $w_{a,t}$ lacks any trend. We call it $\epsilon_{a,t}$. Thus

$$\log w_{a,t} = \frac{1-\mu}{\mu} (\log z_t y_t + \log s_{a,t}) + \epsilon_{a,t}, \quad (28)$$

We also normalize $\epsilon_{a,t}$ to have a zero mean. Movements in $\epsilon_{a,t}$ may be correlated with technical change and resource allocation, an issue we address below.

Using this equation to remove the unobserved $w_{a,t}$ from the production function, we have

$$\log \tilde{x}_{a,t} = \log A_a + \frac{\theta_a}{\mu} (\log z_t y_t + \log s_{a,t}) + \tilde{\epsilon}_{a,t}, \quad (29)$$

where $\tilde{\epsilon}_{a,t} \equiv \theta_a \epsilon_{a,t}$ is a mean-zero, trendless disturbance term in the production function.

The absence of a trend in $\tilde{\epsilon}_{a,t}$ allows us to estimate θ_a . We use a linear time trend as an instrument in equation (29) to estimate the coefficient on the second term, $\frac{\theta_a}{\mu}$. We recover the true elasticity θ_a from this coefficient by multiplying by the known proportion μ . This adjustment removes the omitted-variable bias that would otherwise cause us to overstate the elasticity.

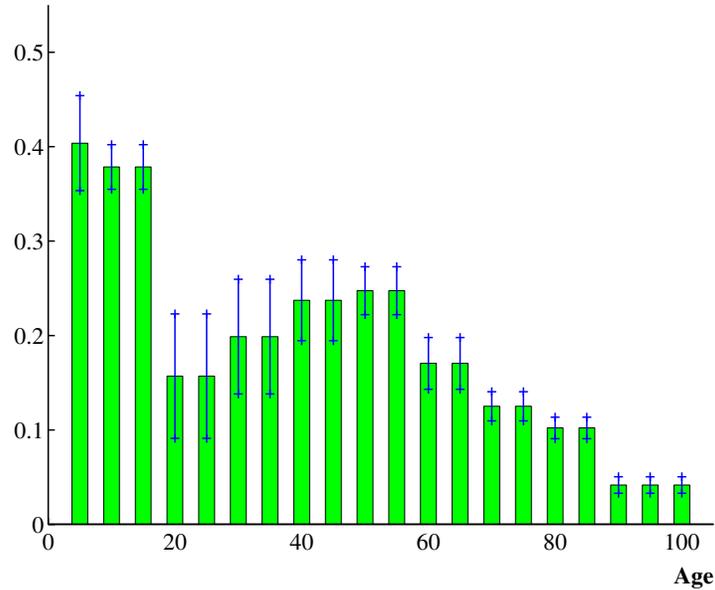
Following this discussion, we use GMM to estimate A_a and θ_a in equation (29). Our two orthogonality conditions are that $\tilde{\epsilon}_{a,t}$ has zero mean and that it has zero covariance with a linear time trend. Because $h_{a,t}$ is strongly trending, the trend instrument is strong and the resulting estimator has small standard errors.

Figure 3 shows the GMM estimates of θ_a , the elasticity of adjusted health status, \tilde{x} , with respect to health inputs, by age category. The groups with the largest improvements in health status over the 50-year period, the very young and the middle-aged, have the highest elasticities, ranging from 0.25 to 0.40. The fact that the estimates of θ_a generally decline with age, particularly at the older ages, constitutes an additional source of diminishing returns to health spending as life expectancy rises. For the oldest age groups, the elasticity of health status with respect to health inputs is only 0.042.

Figure 4 shows the actual and fitted values for two representative age groups. Because the health technology has two parameters for each age—intercept and slope—the equations are successful in matching the level and trend of health status. The same is true in the other age categories.

From these estimates, we can calculate the marginal cost of saving a life at each age. Before turning to these calculations, we provide a summary of the empirical literature on the value of a statistical life (VSL), an alternative measure of the same concept, from the benefit side.

FIGURE 3. Estimates of the elasticity of health status with respect to health inputs



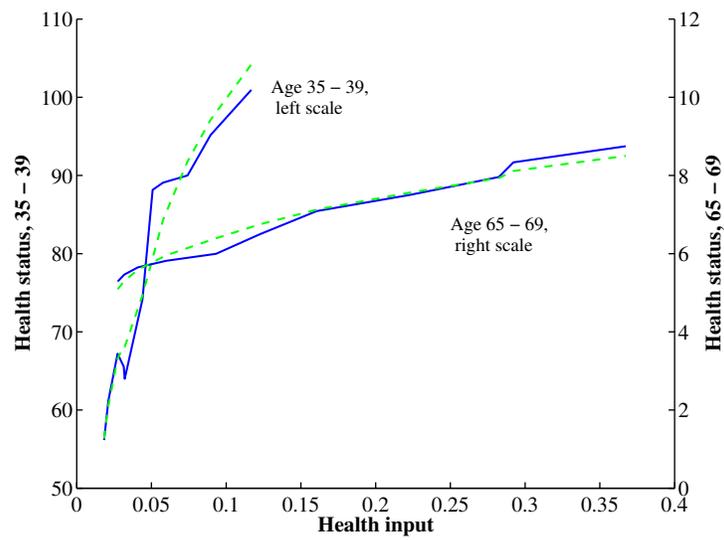
Note: The height of each bar reports our estimate of θ_{α} , the elasticity of adjusted health status with respect to health inputs. The ranges at the top of the bars indicate \pm two standard errors.

6.2. Evidence on the Value of a Statistical Life

In evaluating our results, three dimensions of the VSL literature are relevant. We are interested in (i) the level of the VSL, (ii) the rate at which the VSL changes over time, and (iii) how the VSL varies with age.

Most estimates of the level of the value of a statistical life are obtained by measuring the compensating differential that workers receive in more dangerous jobs. Viscusi and Aldy (2003) provide the most recent survey of this evidence and find estimates of the value of a statistical life that range from \$4 million to \$9 million, in year 2000 prices.

FIGURE 4. Estimation of the parameters of the health technology



Note: The solid lines show actual health inputs h on the horizontal axis and health status, x , on the vertical axis, for two age groups, 35-39 and 65-69, for the period 1950 through 2000. The dashed lines show the fitted values from the estimated production function for health.

Ashenfelter and Greenstone (2004) provide an alternative approach to estimating the VSL. Their research design exploits the fact that states took differential advantage of the relaxation of federal mandatory speed limits that occurred in 1987. They find that a much lower number of \$1.5 million (in 1997 prices) represents an upper bound on the VSL, suggesting that various problems including omitted variable bias and selection problems account for the higher estimates in the labor market literature.

How does the value of life change over time? Recall that a rising value of life is crucial in this model to understanding the rising health share. Unfortunately, there is relatively little empirical evidence on changes in the value of life over time.

Costa and Kahn (2003) appear to provide the first estimates from a consistent set of data on changes in the value of life in the United States. They use decennial census data from 1940 to 1980 and estimate the value of a statistical life in 1980 of \$5.5 million (in 1990 dollars). Moreover, they find that this value has been rising over time at a rate equal to between 1.5 and 1.7 times the growth rate of per capita GDP. Hammitt, Liu and Liu (2000) made a similar study for Taiwan, combining a time series of cross-sections, and they estimate an elasticity of the value of a statistical life with respect to per capita GDP of between 2 and 3. Because life expectancy itself grows relatively slowly, these studies therefore support the key requirement in this paper that the value of a year of life as a ratio to per capita income is rising over time, and provide an estimate of how rapidly the rise occurs.

A different approach to estimating changes in the value of life finds the opposite result, however. In addition to surveying the existing literature that estimates the value of life at a point in time, Viscusi and Aldy (2003) also conduct a “meta-analysis” to estimate the elasticity of this value with respect to income. Looking across some 60 studies from 10 countries, they regress the average value of life estimates from each study on a measure of average

income from each study and obtain an estimate of the elasticity of the dollar value of life with respect to income of about 0.5 or 0.6, with a 95 percent confidence interval that is typically about 0.2 to 0.8. This finding appears to be consistent with several other estimates from different meta-analysis studies that are also summarized by Viscusi and Aldy.

Some additional insight on this issue comes from looking back at our model. Recall that equation (8) in the simple model suggests that the value of life as a ratio to life expectancy is roughly proportional to consumption raised to the power γ . That is, in units of output, the value of a year of life grows with c^γ . One way of thinking about γ is that it is the inverse of the intertemporal elasticity of substitution, which recent empirical work estimates to be less than one. This suggests that $\gamma > 1$, and in fact the values that Costa and Kahn (about 1.6) and Hammitt, Liu, and Liu (about 2 or 3) find accord well with this interpretation. Kaplow (2003) puzzles over the low income elasticity estimates from the meta-analysis literature for a similar reason; the recent empirical work by Costa and Kahn and Hammitt, Liu, and Liu helps to resolve this puzzle, we think.

Finally, we turn to evidence on variation in the value of a statistical life by age. Aldy and Viscusi (2003) summarize the existing empirical literature, which primarily consists of contingent valuation studies. They go on to provide their own age-specific estimates using the hedonic wage regression approach. Qualitatively, they support the contingent valuation literature in finding an inverted-U shape for VSL by age. Quantitatively, their main finding is that the value of life for a 30 to 40-year old is about \$5.5 million while the value of life for a 60-year old is about \$2.5 to \$3.0 million, a gradient of about 1/2 across these age groups.

To summarize, we take the following stylized facts from the VSL literature. First, there is substantial uncertainty regarding the level of the VSL: it could be as low as 1.25 million in the late 1980s, but could range much higher to

numbers like 5 million or more. These numbers are plausibly interpreted as the value of life at some average age, which we will take to be the 35 to 39-year olds. Second, recent estimates suggest that the VSL grows over time, at a rate something like 1.6 or 2 times the growth rate of income. Finally, it appears that the VSL varies with age in an inverted-U pattern, with a relatively gentle slope, falling by about 1/2 between the ages of 35 and 60.

6.3. The Marginal Cost of Saving a Life

Our estimates of the health production function allow us to calculate the marginal cost of saving a life, given the observed allocation of resources. Recall, from the discussion surrounding equation (21), that this marginal cost is $x^2/f'(h)$. With our functional form for the health technology, the marginal cost of saving a life is $h\tilde{x}/\theta$. This expression has a nice interpretation: \tilde{x} is the inverse of the non-accident mortality rate, so it can be thought of as the number of living people per non-accident death. h is health spending per person, so $h\tilde{x}$ is the total amount of health spending per death. The division by θ adjusts for the fact that we are interested in the marginal cost of saving a life, not the average. Importantly, this calculation only involves the health production function. For this part of the paper, the preference side of the model is irrelevant.

Table 1 shows this marginal cost of saving a life for various age groups. We can interpret these results in terms of the three findings from the empirical VSL literature. First, the marginal cost of saving the life of a 40-year old in the year 2000 was about \$1.9 million. In our robustness checks, this marginal cost reached as high as \$2.5 million (in the case where θ_a is identified with the assumption that only 1/2 rather than 2/3 of declines in mortality are due to technical change and resource allocation). These numbers are at the lower end of the level estimates of the VSL from the literature. If one believes the lower numbers, this suggests that health spending was at approximately the right

TABLE 1.
The Marginal Cost of Saving a Life (thousands of 2000 dollars)

Age	1950	1980	2000	Robust Maximum 2000	Per Year of Life Saved 2000	Growth Rate 1950–2000
0-4	10	160	590	(790)	8	7.8
10-14	270	2,320	9,830	(13,110)	150	7.2
20-24	1,170	3,840	8,520	(11,360)	153	4.0
30-34	500	2,120	4,910	(6,540)	107	4.6
40-44	160	740	1,890	(2,520)	52	4.9
50-54	70	330	1,050	(1,400)	38	5.4
60-64	50	280	880	(1,180)	47	5.9
70-74	40	280	790	(1,050)	66	6.2
80-84	40	340	750	(1,000)	123	6.1
90-94	50	420	820	(1,090)	373	5.6

Note: The middle columns of the table report estimates of the marginal cost of saving a life for various age groups. These estimates are calculated as $h\hat{x}/\theta$, using the estimates of θ given in Figure 4 and using actual data on health spending and mortality by age. Standard errors for these values based on the standard errors of θ_a are small. The Robust Maximum column shows the maximum marginal cost we obtained in the various robustness checks described in the text. These values turned out to occur in the case where we assume that 50% of the decline in age-specific mortality is due to the unobserved trend in $w_{a,t}$. The “Per Year of Life Saved” column divides the cost of saving a life by life expectancy at that age. The “Growth Rate” column reports the average annual growth rate between 1950 and 2000.

level as a whole for this age group in 2000. Alternatively, of course, if one believes the higher estimates of the VSL from the literature, the calculation from Table 1 would suggest that health spending for this group was too low.

The second-to-last column of the table provides an alternative view of the marginal cost of saving a life by stating the cost per year of life saved. It shows the cost of saving a statistical life in the year 2000, divided by life expectancy at each age. For example, the marginal cost of saving an extra year of life at age 50 is about \$38,000. Interestingly, the cost of saving a life year in the youngest age category is only about \$8,000, while the cost for

saving a life year for the oldest ages rises to well above \$100,000. We discuss the implications of this finding in a later section.

Finally, the last column of the table shows the growth rate for the marginal cost of saving a life. Since the marginal cost is $h\tilde{x}/\theta$ and θ is constant over time, these growth rates do not depend at all on the estimates of θ . The growth rates are very high, on the order of 5 percent per year. By comparison, the empirical VSL literature finds significantly lower growth rates. Taking income growth to be about 2 percent per year, for example, the income elasticity from Costa and Kahn (2003) of about 1.6 suggests that the VSL grows at a rate of $2 \times 1.6 = 3.2$ percent per year. This implies that the value of life in 1950 or 1960 would have been much higher than the marginal cost of saving a life. Therefore, the U.S. may have been spending too little on health prior to the most recent decade, even taking the level of the VSL from the lower end of the estimates.

7. ESTIMATING THE PREFERENCE PARAMETERS

We present results for two approaches. The first treats the observed levels of health spending as optimal and estimates the preference parameters. The second estimates preference parameters from the evidence in the empirical VSL literature; it implies that health spending was inefficiently low until the end of the 20th century.

7.1. Treating Observed Health Spending as Optimal

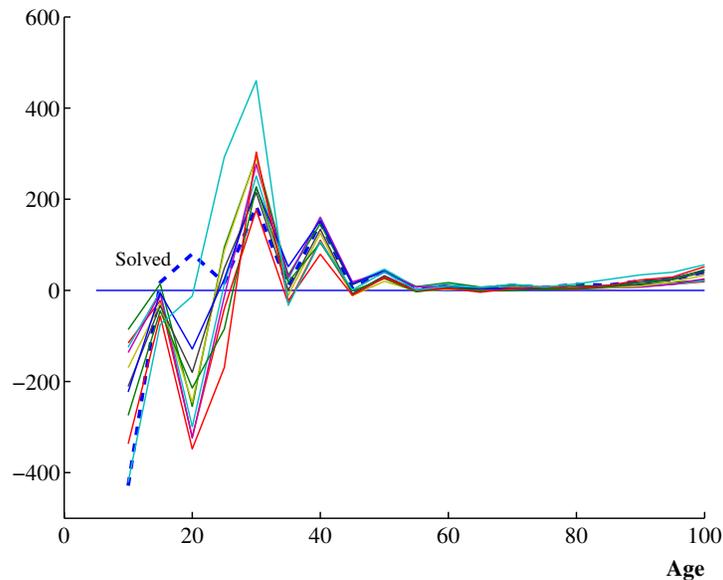
Our model contains the following preference parameters: the discount factor β , the base levels of flow utility $b_{a,t}$, the consumption parameter γ , the quality-of-life parameter σ , and the weighting parameter α . For the moment, we consider the case where health status does not affect flow utility so that $\alpha = 0$. We will reintroduce quality-of-life shortly.

We have explored a variety of parametric restrictions on the base utility, $b_{a,t}$. These include making it a constant for all ages and years, making it vary by age, and giving it a trend over time. The evidence in favor of age effects is strong. There is evidence of trends in base utility, but not at the same rate for different age groups. We have not found a useful parametric restriction—candidates such as a set of age effects and a set of time effects result in sufficiently large residuals that the other parameters take on improbable values.

Accordingly, we treat the values of $b_{a,t}$ as parameters themselves, without imposing any restriction. Because there is one of these parameters for each data point, estimation is a matter of solving for the values, not minimizing a GMM norm or other criterion. Further, this means there are not enough equations to estimate the other two parameters, β and γ . We use outside evidence on these parameters before solving for the values of $b_{a,t}$.

For the curvature parameter of the utility function, γ , we look to other circumstances where curvature affects choice. Large literatures on intertemporal choice (Hall 1988), asset pricing (Lucas 1994), and labor supply (Chetty 2005) each suggest that $\gamma = 2$ is a reasonable value. Recall that higher values of γ lead to faster growth in the value of life and therefore would deliver even more rapid growth in the health share than what follows. With respect to the discount factor, β , we choose a value that is consistent with this choice of γ and with a 5 percent real return to saving. Taking consumption growth from the data of 2.08 percent per year, a standard Euler equation gives an annual discount factor of 0.992, or, for the 5-year intervals in our model, 0.963.

Given the data and the values of θ_a , β , and γ , we first calculate the implied value of life from equation (21) and then recover the base levels of utility from a rearranged version of equation (22). Figure 5 shows the results of the calculations. Each line portrays the base level of utility for every age group in a particular year, for the 11 years at 5-year intervals from 1950 though 2000.

FIGURE 5. Estimates of base flow utility, $b_{a,t}$ 

Note: Each line shows the cross section of base levels of utility in a given year. The periods cover 5 years each from 1950 through 2000. The heavy dashed line labeled “Solved” reports the set of base values inferred from the value of life in 2000 according to the model.

The lines share a common pattern—negative flow utility in the youngest group and usually in the second-youngest group, and also negative flow utility for teenagers. Negativity of flow utility does not contradict any principles of the model. The motivation for continuing to live is to capture next period’s value of life. Negative flow utility marks a difficult period of life that people choose to live through so that they can enjoy later periods with positive utility. For older people, flow utility stabilizes at a common, lower positive level over all periods. Flow utility rises somewhat for the very elderly.

Alternatively, we can interpret the solved values for $b_{a,t}$ as the residuals from the first-order condition in a model with a constant b . Economically, they arise because the marginal cost of saving a life—the right side of equation (21),

with values shown in Table 1—varies considerably more across ages than the value of life on the preference side would in the absence of variation in b . That is, with a constant b across ages, the value of life on the preference side—the left side of equation (21)—turns out to be relatively flat across ages. For example, consider the marginal cost of saving a life reported in Table 1. The way the model interprets the fact that we spend so little on health care for children from 0 to 4 and so much on those between 5 and 9, relative to the marginal mortality reductions from spending, is by having a substantially lower b for the younger group.

In the alternative interpretation of the estimates of $b_{a,t}$ as residuals, they could be seen as measures, at different times, of the misallocation of health care. The institutions that govern the delivery of health care may systematically fail to take advantage of opportunities to reduce infant mortality, for example. This interpretation helps explain our finding that the $b_{a,t}$ do vary over time, contrary to the hypothesis that they are unchanging parameters of preferences.

These calculations provide estimates of the base level of utility during the historical period. For our projections for the next 50 years, we need future values of the base utility parameters. For this purpose, we make use of additional information, namely the level of the value of life in utility units from equation (21) in the last historical year, 2000. This level information is not used in the calculation of the historical values of $b_{a,t}$ from equation (22), which is in difference form. To make use of the level information, we hypothesize that $b_{a,t}$ will not change over the future from its values in 2000. This hypothesis makes sense, because there is no systematic trend in the historical values in Figure 5. Then we proceed in the following way: When we solve the model for the years 2000 through 2095, we treat b_a as a set of unknowns to solve and then require that the model solution match the value of life in 2000. The heavy dashed line in Figure 5 shows these solved values.

Except for the more erratic values for the younger groups, the match is quite good.

7.2. Matching the Earlier Value of Life Estimates

As an alternative approach to estimating the preference parameters, we drop the assumption that the observed data are generated by maximizing social welfare given our estimated health technology. Instead, we take the age-specific spending data and the consumption data as given and compute the value of life at each age, $\beta v_{a+1,t+1}/u_c$, from these data. For future values of health spending by age, we project the existing data forward at a constant growth rate. Until the year 2020, this growth rate is the average across the age-specific spending growth rates. After 2020 we assume spending grows at the rate of income growth. The rate must slow at some point; otherwise the health share rises above one. Our results are similar if we delay the date of the slowdown to 2050.

We then estimate a constant and common value $b_{a,t} = b$ and the curvature parameter γ to match some estimates from the VSL literature. Our baseline scenario features a value of life for 35–39 year olds of \$2 million in 1987. We project this back to 1950 and forward to 2000, using a growth rate of $1.6 \times 2.31 = 3.70$ percent per year, based on the Costa and Kahn income elasticity. By matching the value of life for this age group in 1950 and 2000, we obtain $b = 21.637$ and $\gamma = 1.624$ for the case where health status does not affect flow utility (i.e. $\alpha = 0$). Finally, we recalibrate the time discount factor β to an interest rate of 5 percent based on this new value of γ .

7.3. The Quality-of-Life Parameters

To calibrate the quality-of-life parameters σ and α , we draw upon the extensive literature on quality-adjusted life years (QALYs), elicited by surveying sick and healthy people, medical experts, and others—see Fryback et al.

(1993) and Cutler and Richardson (1997). This work focuses on the QALY weight, the flow utility level of a person with a particular disease as a fraction of the flow utility level of a similar person in perfect health. Surveys ask people what probability p of perfect health with probability $1 - p$ of certain death would make them indifferent to their current health or what fraction of a year of future perfect health would make them indifferent to a year in their current health status. Both of these measures correspond to the relative flow utility in our framework.

Cutler and Richardson (1997) estimate QALY weights by age. With newborns normalized to have a weight of unity, they find QALY weights of 0.94, 0.73, and 0.62 for people of ages 20, 65, and 85, in the year 1990. We use these figures to estimate α and σ . For the case where $b_{a,t}$ is constant across age and time, we use the two equations,

$$\frac{u(c_t, x_{20,t})}{.94} = \frac{u(c_t, x_{65,t})}{.73} = \frac{u(c_t, x_{85,t})}{.62},$$

for $t = 1990$ to solve for α and σ . Because the value of life itself depends on these parameters, we estimate the utility parameters b and γ at the same time. The resulting values are $\alpha = 1.922$, $\sigma = 1.051$, $b = 54.17$, and $\gamma = 1.593$. With four equations and four unknowns, estimation is a matter of solving for the values, so there are no standard errors.

In addition to the QALY interpretation, these numbers can be judged in another way. They imply that a 65 year-old would give up 88 percent of her consumption, and an 85 year-old would give up 93 percent of her consumption to have the health status of a 20 year-old. The intuition behind these large numbers is the sharp diminishing returns to consumption measured by γ . To explain what may seem to be a small difference in relative utilities of .94 versus .73 requires large differences in consumption. Health is extremely valuable.

8. SOLVING THE MODEL

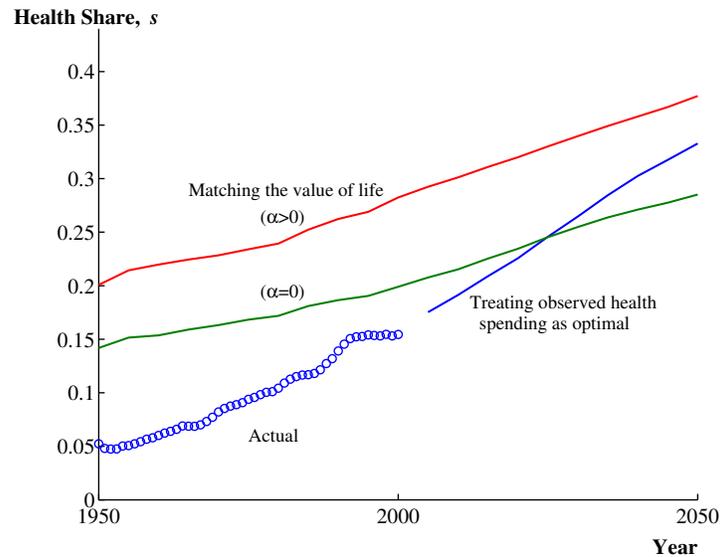
We now solve the model over the sample period 1950 through 2000 and also project the economy out to the year 2050. We solve the model using both of our approaches to calibrating the preferences parameters (the $b_{a,t}$ and γ) and using two approaches to the quality of life ($\alpha = 0$ and $\alpha > 0$). For the historical period, we take resources per person, y , at its actual value. For the projections, we use the historical growth rate for the sample period, 2.31 percent per year. The details for the numerical solution of the model are available from either author's website.

Figure 6 shows the calculated share of health spending over the period 1950 through 2050. A rising health share is a robust feature of the optimal allocation of resources in the health model. The key force at work in the model behind this result is that the marginal utility of consumption in a given period falls rapidly. As the U.S. gets richer and richer, the most valuable thing people can purchase is more time to live.

The figure shows a substantial difference between projected health shares for the two approaches. Our first approach matches the actual health share between 1950 and 2000 exactly. The projection based on that approach implies a rapidly growing health share in the future, reaching 33 percent in 2050. The second approach, based on the VSL estimates in the literature, produces a much flatter health share. Fundamentally, this slower rate of increase is driven by the lower value of γ (1.6 versus 2.0) used in our second approach; recall that γ governs the growth rate of the value of life and therefore determines the growth rate of the health share. This second approach suggests underspending on health for the last 50 years and generates a health share that reaches 29 percent in 2050.

We conduct a number of robustness checks to illustrate how our benchmark results change when key parameter values are varied in plausible ways. For example, Figure 6 also shows what happens when health quality affects utility.

FIGURE 6. Simulation Results: The Health Share of Spending

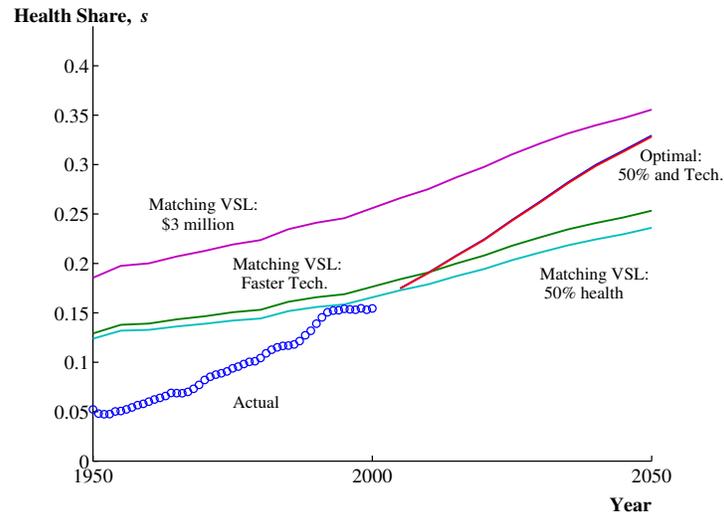


Circles “o” show actual data for the health share. The steeply-sloping line for the period 2005-2050 show the projected health share assuming $\gamma = 2$, where the b_a preference parameters are inferred from treating the historical data as if it were generated by the model. The gently sloping lines for the period 1950-2050 show the hypothetical historical and projected share for preferences inferred from the VSL literature (e.g. $\gamma = 1.62$). Within these two approaches, the upper line corresponds to the case that includes a quality-of-life term ($\alpha > 0$), while the lower line does not ($\alpha = 0$).

Our calibration of α and σ for this case implies a high willingness to pay for health quality. As a result, overall health spending is higher in this scenario. While our benchmark case leads to an optimal health share of just under 20 percent in 2000, allowing for quality of life in utility raises the share to 28 percent. The overall trend in the health share is quite similar.

Figure 7 shows several other robustness checks. Allowing for technical change in the health sector to be one percentage point faster than in the rest of the economy or reducing the share of mortality decline explained by technical change and resource allocation from 2/3 to 1/2 deliver relatively

FIGURE 7. Robustness Checks: The Health Share of Spending

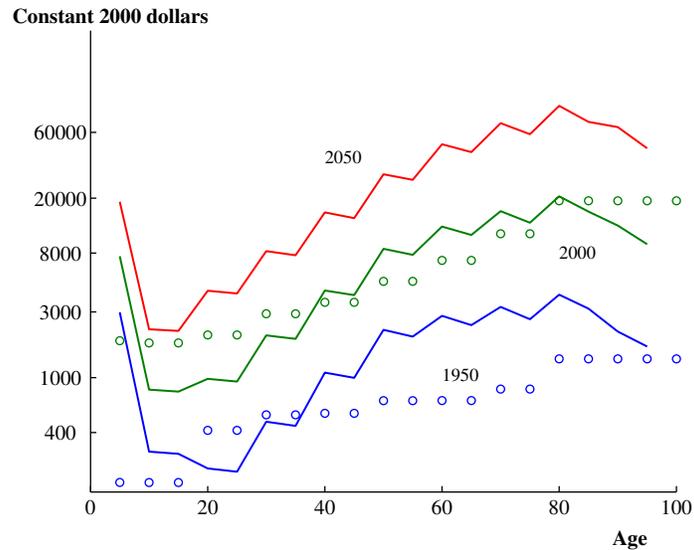


Circles “o” show actual data for the health share. This graph shows five alternative simulations. For two of these alternatives, “Faster Tech.” and “50% health,” we consider both the approach that treats observed spending as optimal and the approach that matches a value of life in 1987 of \$2 million. “Faster Tech.” assumes that technical change in the health sector is 1 percentage point faster than in the rest of the economy. “50% health” assumes that 1/2 of the decline in age-specific mortality (rather than our baseline value of 2/3) is due to technological change and increased resource allocation. Finally, the fifth case matches a value of life in 1987 for the 35–39 year olds of \$3 million.

similar results. In both of these cases, less of the decline in age-specific mortality is due to health spending, so the estimates of θ_a in the production function are smaller. Since health spending runs into sharper diminishing returns, the overall health share of spending is lower. These simulations suggest that the observed share in the year 2000 was roughly optimal.

Alternatively, another robustness check in the figure assumes the value of a statistical life is \$3 million dollars in 1987 rather than \$2 million. This means the marginal benefit of health spending is higher, so the simulation delivers

FIGURE 8. Health Spending by Age

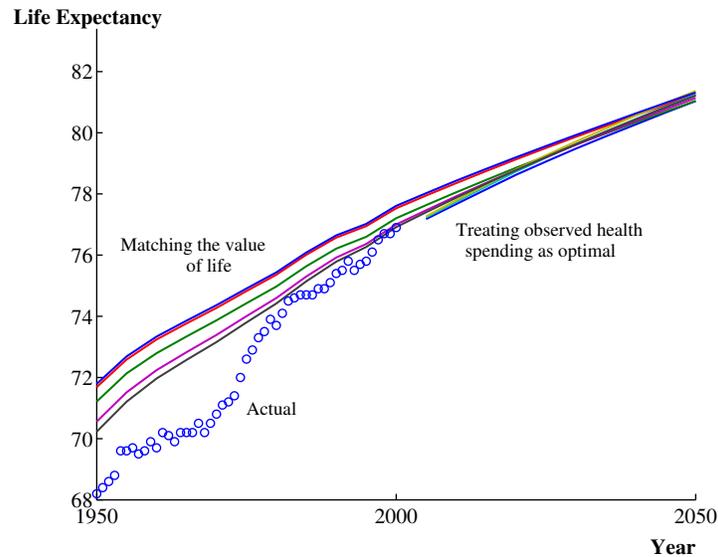


Note: Circles denote actual data and solid lines show simulation results for the baseline scenario in which b and γ are chosen to match estimates from the VSL literature.

a substantially higher health share. In 2000, for example, the optimal health share is 26 percent, and it rises to 36 percent by 2050.

Figure 8 examines the micro data underlying the health share. This figure shows actual and simulated health spending by age, for 1950, 2000, and 2050 for our second approach in the baseline scenario (in the first approach, actual and simulated spending are equated by construction). A comparison of the results for the year 2000 shows that actual and optimal spending are fairly similar for most ages, with two exceptions. Optimal health spending on the youngest age group is substantially higher than actual spending: given the high mortality rate in this group, the marginal benefit of health spending is very high, as was shown earlier. Similarly, while optimal health spending generally rises until age 80, it declines after that point. It is worth noting in

FIGURE 9. Simulation Results: Life Expectancy at Birth



See notes to Figures 6 and 7. Life expectancy is calculated using the cross-section distribution of mortality rates at each point in time.

this respect that the underlying micro data we use for health spending groups all ages above 75 together, so we do not know what the actual pattern of spending looks like above the age of 75.

Figure 9 shows the actual and projected levels of life expectancy at birth for all eight of our simulation runs. The first thing to note in the figure is the overall similarity of the life expectancy numbers. Because there are such sharp diminishing returns to health spending in our health production function, relatively large differences in health spending lead to relatively small differences in life expectancy. A second thing to note is that the projected path does not grow quite as fast as historical life expectancy. The reason is again related to the relatively sharp diminishing returns to health spending that we estimate.

9. CONCLUDING REMARKS

A model based on standard economic assumptions yields a strong prediction for the health share. Provided the marginal utility of consumption falls sufficiently rapidly—as it does for an intertemporal elasticity of substitution well under one—the optimal health share rises over time. The rising health share occurs as consumption continues to rise, but consumption grows more slowly than income. The intuition for this result is that in any given period, people become saturated in non-health consumption, driving its marginal utility to low levels. As people get richer, the most valuable channel for spending is to purchase additional years of life.

This fundamental mechanism in the model is supported empirically in a number of different ways. First, as discussed earlier, it is consistent with conventional estimates of the intertemporal elasticity of substitution. Second, the mechanism predicts that the value of a statistical life should rise faster than income over time; Costa and Kahn (2003) and Hammitt et al. (2000) find this to be the case. Cross-country evidence also suggests that health spending rises more than one-for-one with income; this evidence is summarized by Gerdtham and Jonsson (2000).

One source of evidence that runs counter to our prediction is the micro evidence on health spending and income. At the individual level within the United States, for example, income elasticities appear to be substantially less than one, as discussed by Newhouse (1992). A serious problem with this existing evidence, however, is that health insurance limits the choices facing individuals, potentially explaining the absence of income effects. Our model makes a strong prediction that if one looks hard enough and carefully enough, one ought to be able to see income effects in the micro data. Future empirical work will be needed to judge this prediction. A suggestive informal piece of evidence is that exercise seems to be a luxury good: among people with

sedentary jobs, high wage people seem to spend more time exercising than low wage people, despite the higher opportunity cost of their time.

As mentioned in the introduction, the recent health literature has emphasized the importance of technological change as an explanation for the rising health share. In our view, this is a proximate rather than a fundamental explanation. The development of new and expensive medical technologies is surely part of the process of rising health spending, as the literature suggests; Jones (2003) provides a model along these lines with exogenous technical change. However, a more fundamental analysis looks at the reasons that new technologies are developed. Distortions associated with health insurance in the United States are probably part of the answer, as suggested by Weisbrod (1991). But the fact that the health share is rising in virtually every advanced country in the world—despite wide variation in systems for allocating health care—suggests that deeper forces are at work. A fully-worked out technological story will need an analysis on the preference side to explain why it is useful to invent and use new and expensive medical technologies. The most obvious explanation is the model we propose in this paper: new and expensive technologies are valued because of the rising value of life.

Viewed from every angle, our results support the proposition that both historical and future increases in the health spending share are desirable. The magnitude of the future increase depends on parameters whose values are known with relatively low precision, including the value of life, how rapidly that value has grown over time, and the fraction of the decline in age-specific mortality that is due to technical change and the increased allocation of resources to health care. Nevertheless, we believe it likely that maximizing social welfare in the United States will require the development of institutions that are consistent with spending 30 percent or more of GDP on health by the middle of the century.

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