RATIONALIZING DIVERSITIES IN AGE-SPECIFIC LIFE EXPECTANCIES AND VALUES OF LIFE SAVING: A NUMERICAL ANALYSIS

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ABSTRACT

Despite general recognition of rising life expectancies worldwide, little attempt has been made to quantify the extent to which individual efforts at health and life protection may account for some of the observed diversities in age-specific life expectancies across individuals and over time. We address these issues via calibrated simulations of a dynamic, life-cycle model of life protection in which life's end is a stochastic event, age-specific mortality risks are endogenous variables, and life protection choices are set jointly with market insurance options: life insurance as well as annuities. A unique feature of our model is that it links mortality risks and private value-of-life-savings (VLS) measures as two sides of the same coin, and allows for systematic variation in both across different age and population groups. Our simulations show that life protection has a non-negligible impact on life expectancy. It can account for a significant portion of observed diversities in life expectancies by age, gender, race, and education groupings, as well as for the wide range of VLS magnitudes previously estimated using the "willingness to pay" approach.

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INTRODUCTION

Despite the persistent upward trend in longevity in the developed world, there has been little systematic attempt among economists to **quantify** the importance of individual efforts at health and life protection in explaining the trend and diversity of age-specific life expectancies across population groups. Studies that address the determinants of life expectancy generally rely on life-cycle models treating life's end as known with certainty (see references in Forster, 2000). Most also estimate reduced-form equations of an underlying theoretical structure, which are not functionally linked to the theoretical structure itself (see references in Gerdtham et al., 1999, and Barlow and Vissandjee, 1999). Expanding on the approach developed in Ehrlich (2000), we attempt to redress these issues through calibrated simulations of a dynamic life-cycle model of life protection where life's end is an uncertain event, life-cycle consumption and savings decisions are influenced by related insurance options, and age-specific mortality risks, hence life expectancy, are endogenous variables. A unique feature of our approach is that it links mortality risks and private value-of-life-savings (VLS) measures as two sides of the same coin over the life cycle and across population groups.

Our key assumption is that age-specific mortality risks can be lowered on the margin relative to biologically endowed levels that continuously rise with age (at least from adulthood), through "self-protective" inputs. These include preventive medical care services, diet and exercise, and myriad safety measures, collectively termed 'life protection' and measured as total **spending** on all these inputs. Individuals can also insure against mortality risks by purchasing both life insurance and annuities at actuarially fair terms. The model's control variables thus include age-specific consumption and bequest (accumulated ordinary savings and life insurance) as independent choice variables, in addition to willingness to spend on life protection. A key co-state variable affecting the latter, hence mortality risks and life expectancy, is the 'shadow price of life protection', also known as the 'value of life saving' (VLS).

As previous literature emphasized (see e.g., Yaari, 1967, Rosen and Thaler, 1975, Davies, 1981, Arthur, 1981, and Philipson and Becker, 1998), recognizing longevity as uncertain can change the standard economic predictions about life-cycle choices depending the availability of annuities and life insurance markets. Treating consumption and bequest along with the risk of mortality itself as endogenous variables raises an analytical challenge, however, because this complex dynamic framework does not yield closed-form solutions. Ehrlich (2000) derived conditional closed-form solutions by treating one of the three endogenous variables as predetermined. In this paper we provide **unconditional** dynamic solutions for all three choice variables simultaneously, using numerical methods. The simulation analysis allows us to project simultaneously age-specific optimal spending on life protection and value of life savings from information concerning observed mortality risks, to account for the interaction between life protection and related insurance options, and to link dynamically optimal bequest by older generations with the initial wealth level of their offspring. More important, the simulation analysis allows us to quantify the extent to which optimal life protection may account for the observed **diversity** of life expectancies across different age and population groups and to project varying private values of life saving measures across these groups.

Our analysis is facilitated by a number of simplifying assumptions, which permit the use of the model's optimality conditions in the simulations. We account for efforts at life protection through an aggregate spending measure, which we calibrate empirically based on preventive medical spending and estimates of related workplace and life-style health-and-life-protective measures. We generally treat life protection as a flow, rather than a stock variable, but we also use our methodology to account for the **durability** of life protection over finite periods. To simplify the numerical valuation of "human wealth" and "non-human wealth" as components of the theoretical private value of life saving, we assume that annuities and life insurance are available to individuals at actuarially fair terms. Notwithstanding these and related simplifications, our calibrated simulations account for a nontrivial portion of observed variations in life expectancies by age and population groups.

Our model's parameters are, in principle, estimable statistically, but the life cycle individual data required for such estimation are not fully available. We rely, instead, on calibrated simulations of our model's basic parameters, based on representative group data, to project age-specific values for all our control and state variables. These offer new insights about our key control and state variables over the life cycle.

Value-of-life-saving estimates (VLS) have so far been derived mainly through regression analyses measuring the "willingness to pay" for marginal reductions in mortality risks, based on "compensating" earnings or price differentials associated with activities posing varying risks to life. But these regressions treat observed mortality risks as **exogenous** variables: Willingness to pay is assessed against environmental risks of which individuals or workplaces are assumed to have no independent control. Our approach treats observed probabilities of mortality over the life cycle and in the cross section as **endogenous** outcomes of optimal life protection. We are thus able to link age-specific life expectancies with VLS and rationalize significant variations in the latter over the life cycle as well as in the cross section (see Viscusi, 1993 and Viscusi and Aldy, 2003).[1] We are also able to assess the relative quantitative importance of specific determinants of the demand for life protection. An important insight is the relative significance of variations in human wealth and the assessed unit cost of life protection efforts in affecting variations in life expectancy and VLS.

We conduct two types of calibrated simulations. In the first, we rely on the observed density functions of age-specific mortality risks for the general population (our benchmark group) or different gender and racial groups, as reported by the *Vital and Health Statistics of the US* [VS], to simulate the model's predictions concerning optimal life protection and impute the corresponding density functions of age-specific "biological" mortality risks. The differences between the realized and projected risks indicate the quantitative impact of life protection on **observed** life expectancy levels.

In the second, we use the imputed biological density function of mortality risks for our benchmark group to project the **actual** mortality risks for different educational groups (for which no VS data are available) and over time. The differences between the projected and observed mortality risks provide an alternative assessment of the model's power to rationalize diversity in life expectancies in the population. Both types of simulations suggest that life protection has a non-negligible impact on the level and diversity of life expectancy. They provide a range of age-specific 'value of life saving' estimates based on differences in projected "willingness to pay" for life protection.

We proceed as follows: Sections I and II introduce our model and iterative procedure. In section III we calibrate our benchmark case. In sections IV and V we conduct simulations explaining life expectancy variations across different groups and over time. We conclude by assessing the model's power to explain the apparent variability in both life expectancies and empirically estimated magnitudes of 'value of life saving'.

I. The Theoretical Model And Its Numerical Solution

The essence of our theoretical approach is the correspondence between efforts to reduce mortality risks, which we call "life protection", and the standard definition of what the literature calls "value of life saving". Under static conditions, the prospect of mortality means facing a pair of conditional outcomes: a consumption plan if alive (G), subject to a wealth constraint (W) net of life-protection outlays (s), G = (W-s) with utility level U(G), or a bequest plan B = (W-s), subject to the same constraints but yielding a lower utility level V(B). The underlying mutually exclusive states of the world are "life" and "death", with probabilities (1-p) and p, respectively. Life protection outlays (s) are designed to lower p, where p(s) is a continuously differentiable and strictly concave function of s, and $p'(s=0) \rightarrow \infty$. Optimal life protection requires as a necessary condition the equality between the marginal cost of life protection and its marginal revenue:

(1) $[-p'(s)] = [(1-p(s))U'(G) + p(s)V'(B)]/[U(G) - V(B)]$.

Equation (1) restates the optimal "self-protection" decision in Ehrlich and Becker [EB] (1972). Taking its inverse value we obtain:

(2) $v(s) \equiv -[1/p'(s)] = [U(G) - V(B))]/[(1-p(s))U'(G) + p(V'(B)]$.

The numerator of (2) defines the difference in utility between being alive or dead and the denominator of (2) defines its marginal cost in utility terms. Their ratio defines the "shadow price of life protection", or the "willingness to pay" for a marginal reduction in the probability of mortality – better known as the "value of life saving" (VLS). Optimal self-protection and VLS, are thus shown to be two sides of the same coin. In EB's model, the self-protection decision is determined jointly with a "market insurance" alternative.

The model we specify and simulate in this paper is a **generalization** of this market-insurance-self-protection paradigm in several ways: it is formulated as a continuous-time, life-cycle consumption prospect subject to stochastic odds of survival to any point in time ("age"), under a given age-earnings profile and an initial wealth level endogenized as the optimal bequest left by an earlier generation. It is also a generalization of the "insurance" problem analyzed in EB in that two types of "market insurance" are recognized simultaneously: insuring survivors' needs in the event of ones' premature death (life insurance), and insuring one's own old-age needs arising from unanticipated longevity (annuities purchase). The availability of a market for actuarial notes allows us to solve for optimal consumption and bequest paths separately over the life cycle, to estimate the "market" value of human wealth under uncertain work horizons, and to link optimal bequest of an older generation with initial wealth of its offspring.

The formal model is outlined in Appendix A. Here we introduce its basic components. We assume that the survival probabilities between any two points in time follow a generalized Poisson process: $p(i,j) = \exp[-\int_i^j f(t)dt]$, where f(t) is the **time-varying** hazard that death would occur at t, given survival to t. Our basic innovation is treating this conditional hazard rate, or "force of mortality", as being controllable on the margin through concurrent life protection inputs involving own time (m), preventive health care and safety measures (M), personal efficiency (E), and general level of healthcare technology θ, i.e., I(t) = I(m(t), M(t); E(t), θ(t)). Life protection lowers the natural, or biological, hazard rate j(t), which continuously rises with age (at least from adulthood), i.e., $\overset{0}{j}(t) > 0$. For convenience, we define the output of life protection in units of mortality rates, so f(t) = j(t) - I(t).

Life protection efforts are subject to diminishing marginal productivity, thus increasing marginal cost, largely because of the finiteness of the human body. The cost of life protection is assumed to be given by $C(t) = cI(t)^{\alpha}$, where c is the cost of providing "one unit" of I(t), and $\alpha>1$. This one-unit cost is generally a function of given health-services market price and medical technology and one's wage and human capital (education) paths, or c(t) = c(Pm, θ, w(t), E(t)), respectively. Since the wage (opportunity cost of time) is itself a function of human capital, w(t)=w(E(t)), and the two have opposite effects on c, we abstract from any drift in c over the life cycle or in the cross section, by invoking a "neutrality" assumption about the net effect of human capital on unit costs.[2]

We assume the existence of competitive markets for actuarial notes (life insurance and annuities) that are actuarially fair at the individual level. This simplifying assumption enables us to treat own consumption, Z(t), and bequest B(t) – i.e., life insurance and accumulated ordinary savings (which survive one's death) – as separate objects of choice, along with life protection. It also enables us to assess the implicit "market" (actuarially fair) value of both human wealth, L(t), i.e., the capitalized value of future earnings net of life-protection outlays, and non-human wealth, A(t), i.e., the annuity-equivalent of all accumulated assets as defined in equations (A.2a) and (A.3a) in

Appendix A.1. The objective function is the maximized (additive) expected lifetime utility having a stochastic end of actual life period, $\tilde{D}$, and specified as:

$$(3)\ J_t(A(t),t;\alpha') = Max_{Z,B,I}\ E\{\int_t^{\tilde{D}} \exp[-\rho(s-t)]U(Z(s))\,ds + \exp[-\rho(\tilde{D}-t)V(B(\tilde{D}),t)]\},$$

where $U(Z) = (1/k)Z^k$, $V(B,t) = [n(t)/k]B^k$, $0<k<1$ to assure concavity, ρ is a subjective discount factor, and α' is a parameters vector. The expectation operator E is defined over the density function of the endogenous mortality risks. Since age at death $\tilde{D}$ is stochastic, the optimization problem must be defined over some planning horizon $D \leq \infty$. The boundary conditions restrict annuity wealth, A(t), to be exhausted at D (see equation A.4).

To facilitate the dynamic simulations, the model treats life protection as a flow variable. In section IV.C.1, however, we simulate the model by allowing life-protection to have a **durable** effect on future mortality rates. Also, we do not model morbidity risk (health) as being distinct from mortality risk (see Ehrlich, 2000). Part of the material impact of life protection on morbidity is captured, however, by the actual earnings data we use in our simulations, W(t), which account for labor time lost to illness. To mitigate the omission of health as utility, however, we also conduct simulations in which the value of healthy time is imputed as part of our definition of "full earnings" (see section IV.B.5).

Equation (3) allows for "bequest" just as a financial legacy. It thus implicitly includes in "consumption" any investments a family head makes in raising and educating children, who provide altruistic benefits as well as informal-care and support at old age. The accumulated financial wealth we derive should thus be interpretable as accounting, in part, for such parental investments. In addition, the model assumes all annuities to be private, although in practice annuity income and related taxes come largely from social security and Medicare. In our baseline simulations A(t) thus accounts, in principle, for social security and Medicare wealth as well. To partially correct for these omissions, in section IV.C.2 we specify social security wealth as a separate component of wealth.

The first-order optimality conditions are given in Appendix A. The model's parameters are the age profiles of the biological mortality density j(t), the real wage profile, w[E(t)], and the time-invariant parameters associated with the real return on capital (r), and the utility and health-production cost functions (ρ, k, n, c, α) as defined above and in Appendix A. The chosen "control variables" are the time-varying paths of life protection, I(t), consumption, Z(t), and transferable assets, B(t), under a given planning horizon ($D \leq \infty$). These dictate the resulting "state variables" paths – net human and non-human wealth, L(t) and A(t), and the mortality density function f(t), hence life expectancy $T^*(t)$.

A key co-state variable driving our analysis is the shadow price of a marginal reduction in the force of mortality, or the private value of life saving, v(t), solved as

(4) $v^*(t) = (1/k)L(t)+[(1-k)/k][A(t)-B^*(t)] = z(t)[A(t) + L(t)] - A(t)$,

with z(t), A(t) and L(t) defined in equations (A.2a), (A.3a), and (A.13) of appendix A.

The closed-form solution in equation (4) represents a dynamic version of the static VLS in equation (2). Like equation (2) it is conditional, however, on the mortality density f(t), which affects the values of z(t), L(t) and A(t) and is an endogenous outcome of optimal life protection, $I^*(t)$. The latter is found by equating the value of life saving with its marginal cost, $v^*(t) = \alpha c I^*(t)^{\alpha-1}$. The age-varying VLS levels can thus be inferred from the **optimal** "willingness to pay" for a marginal increase in the output of life protection

(I*(t)) at different age levels, which is determined jointly with the optimal consumption and bequest paths, Z*(t) and B*(t) (see Appendix A).

An intriguing aspect of equation (4) is the importance of human, relative to non-human, wealth in determining the optimal, age-specific VLS. The intuitive reason is that human-wealth can be realized at any given age only upon survival to that age. It thus has a greater weight in determining the optimal path of life protection efforts over the life cycle.

It is impossible to obtain closed-form solutions for all endogenous variables. Ehrlich (2000) solved the system conditionally by taking life protection to be predetermined (see Appendix A.2). Here we derive **unconditional** solutions for all choice variables through an iterative procedure described below. The stochastic dynamic programming method used to solve the model (see, e.g., Judd, 1998) produces **consistent** life-cycle paths of these endogenous variables starting from any given age, t, conditional on survival to t.

II. THE ITERATIVE METHOD

We combine our conditional closed-form solutions for consumption, bequest, and the value of life-saving function along with the first-order condition for optimal life protection, as given in Appendix A, to derive unconditional solutions for all choice variables through an **iterative** procedure described in Appendix B.

As a starting point, we need to explain our treatment of mortality rates, which is a key input in our iterations. No data are available on "biological" rates, j(t). What we observe in practice are the actual mortality rates f(t), which we take to be the difference between the biological rates and the impact of life-protection, or f(t) = j(t) - I(t). While we could start the iterations with any assumed natural mortality rates, in our benchmark model we calibrate our simulations by taking the **observed** average mortality rates for the entire US population as the solution for f(t), and impute the optimal age-profile of self-protection activity that accounts for it. We thus recover the **implicit biological** mortality density j(t) for that group. For specific population groups, we can similarly impute the group-specific biological densities from the observed ones, if available, or use the imputed biological density for the benchmark group as the actual densities of the specific-groups.[3]

The simulations we conduct on the basis of this iterative method for alternative calibrations converge quite rapidly and smoothly under widely different values of the model's underlying parameters. In most cases, the system converges to a stable solution after just 4 or 5 iterations. The solutions are also found to be locally unique, since when we use different starting values (initializations) of I(t) (see step A in Appendix B), the system converges to the **same** set of numerical solutions for all endogenous variables.

III. CALIBRATING THE MODEL

We attempt to calibrate the basic parameters of the model using actual data and independent studies. Some of our calibrations apply to the entire population (our benchmark group) while others vary across population groups, based on available data.

A. Age-Specific Mortality Density

We start with the **observed** profile of average age-specific mortality rates, f(t), for the US population in 1996, which we take from VS (1999; Series 2, No. 129, Table 1). The VS life table contains **discrete**, and somewhat noisy annual death rates from age 0 to 100. To smooth out this annual series, converting it to a continuous density, we assume that f(t) follows a "local" linear trend within each year. We also take the growth rate of f(t) at time t to be the average growth rate of f(t) over the time periods t-1 and t+1. The constant term of the projected linear trend is then derived from the constraint that the **integral value** of the affected fatality density should equal $-\ln(1-q_t)$, where q_t is the death rate at time t.

One remaining problem is that, while life tables end at age 100, we need to project mortality rates up to age 107, and even up to 150 in our sensitivity analyses (see section III.E). Following the technical recommendation in the VS report, we extend our death rate series beyond age 100 using the relationship $1-p(t-1,t) \equiv q_t = q_{t-1}e^{k_t}$, where $k_t = k_{85} + s(t-85)$, and the report's recommended values for k_{85} and s.

B. The Earnings Profile

The age-earnings profiles we use are the average labor earnings of employees and self-employed workers of different age groups as well as of different sex and schooling levels in 1996, as listed in the *Statistical Abstract of the United States* [SAUS] *(1998*, Table 246). These profiles, W(*t*), are smoothed out by fitting a cubic linear trend, because market wage data are given only up to age 65, and terminated at age 80 on the assumption that earnings are negligible past that age. While our theoretical model is interpretable as relating to "full-earnings", including the value of healthy time in both life protection and home production, we allow for arbitrary estimates of the latter only as part of our comparative dynamics and sensitivity analysis. In our baseline simulations we use reported labor earnings and monetary spending to calibrate W(t) and the unit cost of life protection.

C. The one-unit Cost of Life Protection

An important challenge is estimating the "one-unit" cost of self-protection, c. The estimate we arrive at for our baseline group is c= 3.4 "units".[4] We calibrate this parameter, based on our specification of the life-protection cost function, to ensure that our projected value of the average annual life-protection spending per person over the middle-age bracket 40 to 49 would account for available data on three major categories of life-protection spending (regardless of source of financing): "preventive" medical care, work-place safety costs, based on mandated OSHA requirements, and private spending on diet and exercise representing preventive efforts associated with life-style choices.

Medical care expenditures by age are available from the *Medical Expenditure Panel Survey* of 1996. We distinguished discretionary "preventive care", which protects a person in a healthy state from reaching a potentially acute state of illness, from "remedial care", which is spent in a state of illness to avert potential life-threatening conditions, since theoretically, our life-protection spending is essentially discretionary. Based on an expert physician's assessment, we set the preventive care portion of total spending at 46.27%, allowing for a range of deviations around this figure in our actual simulations.[5] Assessments of the total cost of mandatory OSHA regulations per worker are hotly disputed in the literature – we have thus used a conservative lower-bound assessment, taken from Harvey (1998), by which this cost constitutes 0.866 % of average annual wages. We extrapolated the annual spending on diet and exercise using Nachtrieb (2003).[6]

D. Other Parameters

Since there are no available data on individual financial endowments at age 18, (A(0)), we impute this variable **iteratively** via our dynamic simulation procedure so as to match the expected value of **bequest** left by a parent who dies one generation (25 years) ahead (i.e., at age 43), discounted by the average mortality rates of parents through that age. We make the same adjustment to A(0) whenever we vary any of our basic parameters. For our baseline case, this method sets the financial endowment at A(0) = \$6,315 (see IV.A).

We set the elasticity of utility with respect to consumption k in equations (3) and (A.9) to be 0.5, so the degree of relative risk aversion, d = (1-k), is 0.5 as well. The implied inter-temporal elasticity of substitution in consumption (σ) is thus 2, which falls within the range of estimated values of σ in many econometric studies. The intensity of utility derived from bequest, n (see equation (A.10) in Appendix A), is calibrated to be constant at 1.2.[7] Theoretically, n is the square root of the ratio of bequest to consumption in our model (see equations (A.14) and (A.15) in Appendix A). The *Statistical Abstract of the United States* for 1998 sets the total ordinary life insurance in force in 1996 (which we take to be the main indicator of intended bequest) at \$8.337 trillion, and personal consumption at \$5.208 trillion, producing a rounded ratio of 1.5, and justifying n=1.2. The real interest rate, r, is calibrated to be 3.2%, a conservative estimate of the long-term real rate of return on a total portfolio of financial and non-financial assets,[8] and the time preference parameter, ρ, is set at 1.5%. This variable is calibrated so as to make our benchmark simulation of the non-human annuity-wealth accumulation per family head approach the level of mean family wealth, as gleaned from official statistics (see fn. 9).

We set the planning horizon to start at age 18 because market wage income prior to this age is quite low, and most juveniles do not make independent consumption, health, and bequest choices. Starting our simulations at age 18 (or 25 in section V.C) supports our treatment of schooling in this paper as a largely predetermined variable.

E. The Planning Horizon.

A critical parameter to be selected is the terminal point of the planning horizon, D. In principle D is infinite, as we place no upper limit on biological survival. We choose a finite horizon, however, because our stochastic dynamic optimization problem and our simulations require a finite D, and because we expect that the rising biological mortality risks with age, and the finiteness of human wealth make it inexpedient to plan on potential survival beyond some distant, but finite age. Yet, to specify such an age **a priori** defeats the basic premise of the model, which treats survival probabilities as a choice variable.

A logical remedy would be to set D to be sufficiently distant so that the simulation results would be **practically invariable** to its value. This can be done by computing the maximized expected utility from living J(D) (see equation (3)) at alternative terminal planning dates. For any given set of parameter values, we plot J(D) as a function of D. The results, based on our benchmark parameter set, are striking. Figure 1 shows that although J(D) is a monotonically increasing function of D, it becomes asymptotic to a finite level. Specifically, J(D) first rises sharply at young age levels, then more slowly at older age levels, but becomes essentially flat after age 100. The conventional stopping rule we adopt sets D at the point where the increase in J(D) falls below 10^{-5} percent. This occurs at age 107. Indeed, higher values of D result in virtually **no changes** in the solutions for the model's endogenous variables, and this is the case under alternative parameter values. Optimal life expectancy is thus finite as well, as it is necessarily lower than D. Furthermore, our selected value of D = 107 is not inconsistent with the fact that persons over the age of 100 are currently the fastest growing age group in the US.

IV. SIMULATION RESULTS

A. The Baseline Case

The simulation results for our benchmark group (the total population) are presented in Table 1. Figures 2-6 also present the simulated age-profiles of key variables: the value of human and non-human wealth, the value of life saving, v(t), the actual vs. imputed "biological" mortality rates, f(t) v. j(t), and the profile of the age-specific (remaining) life expectancy $T^*(t)$. We skip the age profiles of consumption (Z) and bequest (B), which are proportionally related ($B^* = n^{1/d}Z^*$ by equations A.14 and A.15) since the rate of growth of both is a constant, $[(r-\rho)/(1-k)]$, as can be shown using equations (A.7) and (A.5).

Figure 2 shows the age-specific (remaining) expected net human wealth L(t), representing the capitalized sums of remaining "net earning flows" (the difference between employment earnings and expenditures on self-protection), discounted for both the cost of future funds and mortality risks (see equation A.3a). While the observed earnings profile peaks at age 49, human wealth peaks at age 29 and declines continuously afterwards. This profile reflects both increasing expenses for life protection and increasing fatality rates. Indeed, our simulated value of human wealth in Figure 2, based just on **market** wages, becomes negative after age 80, which is our last age with (projected) positive earnings. In the following section, however, we also present simulations based on "full earnings" adjustments, designed to capture the value of healthy time in "home production" as well.

The annuity-equivalent non-human wealth age profile $A(t)^*$ (Figure 3), defined in equation (A.3a), has the usual inter-temporal humped shape, starting at an endogenously solved bequeathed endowment at age 18, A(0), and falling back towards A(D)=0 at the end of the **planning** horizon. We link iteratively A(0) to optimal bequest from an older generation (25 years apart). In our benchmark case, planned bequest (transferable savings and life insurance) for a 43-year old parent is projected at $31,575. However, since only 20% of the parent's generation would expire by age 43, we take 20% of $31,575, or $6,315, to be our benchmark inheritance level of an average offspring at age 18 (in a two-parent family with 2 children). It is important to note that, given our perfect capital market assumption, this figure stays the same regardless of whether the parent's death and timing of bequest occur at an age younger or older than 43, as long as the age gap between parent and offspring remains 25.[9]

Figure 4 shows the equilibrium age-specific 'value-of-life-saving' profile, v*(t), defined in equation (A.13). Since the optimal value of life saving is also equal to the equilibrium marginal cost of (or "willingness to spend on") life protection, or $v^*(t) = \alpha c I^*(t)^{\alpha-1}$ (we set α=2 in our baseline simulation), the v*(t) and I*(t) age-profiles share the same shape, and we therefore skip a separate presentation of I*(t). The v*(t) profile is also hump-shaped, starting at a low level and falling to zero at the end of the planning horizon, D. In Figure 4, v*(t) starts at $1.191 million at age 18, peaks at $1.435 million at age 38, and falls sharply after 48. This reflects the influence of the changing magnitudes of human wealth and non-human wealth, as well as interest rate level, the bequest motive and the assumed degree of relative risk aversion (see Table 2). Although the value of life saving falls to zero at the end of the planning horizon, it remains quite high about age 65 or even the life-expectancy age of 77 at age 18 (see Table 1).

This pattern is somewhat different from the shape of the "value of life-extension" profile in Ehrlich and Chuma (EC) (1990), which is monotonically increasing with age, essentially because our model recognizes the potential of death at any age over the life cycle, rather than at an artificially assumed **certain** (though endogenous) age. Since the value of lowering the probability of mortality at a given age is influenced by the expected length of one's remaining (uncertain) life span, which shrinks as one advances in age, the value-of-life-saving profile in this analysis is more closely related to that of the 'value of healthy life' in EC's paper. Indeed, an interesting feature of the simulated $v^*(t)$ profile in Figure 4 is that it remains fairly flat about the age in which it reaches its peak value. For the baseline case, $v^*(t)$ varies less than 2.5% from its peak between age 30 and 46. This remains the case for different parameter values of n and k, or r, except that the flat segment covers a different range of ages. For r=4%, for example, $v^*(t)$ varies less than 2.5% from its peak at age 55 between the years 44 and 65.[10]

Figure 5 enables us to explore a central theme of the paper – the quantitative impact of life protection on the age-specific fatality rates and life expectancies – by comparing the actual and our imputed ("biological") fatality rates. The plot reveals, not surprisingly, a diminishing importance of life-protection efforts in affecting rising mortality risks as the biological risks increase significantly, especially at older age levels. Over the average life span – ages 18 to 77 (the actual life expectancy at age 18) – average life protection, $\bar{I}(t)$, is seen to account for **17.81%** of the projected average "biological" mortality risk, $\bar{j}(t)$.

To complete the simulations, we also provide in Table 1 and Figure 6 the age profiles of life expectancy $T^*(t) = \int_t^D \exp[-m(t,u)]f(u)(u-t)du$, where $m(t,u) \equiv \int_t^u f(s)ds$, based on both our estimated biological, and the actual, age profiles of mortality rates. The gap between the two indicates that life protection accounts for about 3.426 years, or a 6.16% improvement over our imputed "biological" life expectancy of our benchmark group at age 18, and about 0.065 years, or 0.66% at age 77.[11]

B. Comparative Dynamics and Sensitivity Tests

The simulations we conduct to ascertain the comparative-dynamic implications of our model are based on our **imputed biological**, rather than the observed, age-specific mortality rates for the benchmark group, since the latter are endogenous in our model. The key results are summarized in Table 2. While all our reported simulations begin at age 18, we have also tested the sensitivity of our results to a starting age of 22, partly to justify our treatment of schooling as a predetermined variable for our benchmark group. The results concerning our projected mortality risks remain virtually unaffected by this change (to the 4th decimal point), and the differences concerning other endogenous variables are less than 1% at comparable ages. Comparative dynamic effects are assessed by varying the level of each of our parameters 25% above and below its **calibrated value**.

B.1 <u>Changes in relative risk aversion.</u>

Since a lower k implies a higher degree of relative risk aversion, we expect it to lower exposure to life-risking activities, i.e., to increase the demand for life protection. Indeed, greater relative risk aversion significantly raises the value-of-life-saving level (see eq. 4). Changes in k may have little quantitative effect on net human wealth, L(t), because of their opposite impacts on f*(t) and on spending on life protection (see eq. A.3a). The impact on non-human wealth A(t), however, can be higher - greater relative risk aversion (a lower k) increases consumption at young ages while reducing the optimal rate of growth of consumption and bequest, thus savings and asset accumulation.

Table 2 bears out these predictions. The peak $v^*(t)$ value changes from \$1.186, to \$1.435, and to \$1.823, million at age 38 as k falls from 0.625, to 0.5, and to 0.375, respectively. Similar changes in k also have their predicted effect on mortality risk. As k falls from 0.625 to 0.375, the gap between the actual and "biological" mortality risk rises from 2.817 to 4.419, and life expectancy at age 18 rises from 58.49 to 60.09.

B.2 <u>Changes in unit cost and marginal productivity of life protection.</u>

Table 2 indicates that larger values of c, either because of higher medical care prices or a less effective medical care technology (θ), significantly lower self-protection and life expectancy, especially at age 18, but they marginally **raise** the value of life saving at all ages. This result is not paradoxical. An increase in c generates opposing effects on the demand for self-protection and its marginal cost, thus the value of life saving, $v^* = \alpha c I^*(c)^{\alpha-1}$ (see equation A.6). A higher one-unit cost of self-protection reduces the demand for self-protection spending, but VLS can fall or rise as a result, depending upon whether the elasticity of demand for life protection with respect to c exceeds or falls short of 1. Our simulations indicate that life-protection efforts, $I^*(c)$, fall by almost the same proportion as an increase in c, and therefore the net effect of a rise in c is to slightly **increase** VLS: At its peak, v* increases from \$1.432 million at age 38 to \$1.437 million at age 38 as c rises from 2.55 to 4.25. Average **spending** on life protection, cI^α (α=2) falls by about 50% at age 38, while life expectancy at age 18 falls from 60.29 to 58.39.

The impact of an increase in the marginal productivity of life protection due to a change in the parameter α of the cost function $C(t) = cI(t)^{\alpha}$ (see section I), has, of course, just the reverse effect to that of a higher unit cost of life protection, c.[12]

B.3 Changes in the real interest rate.

Theoretically, an increase in r lowers human wealth and increases the rate of accumulation of non-human assets. The impact on the value of life saving, which is a non-linear function of both components of total wealth (see equation A.2a) is thus two-fold: a higher r can increases the value of life savings at older ages, where A(t)/L(t) is relatively high, but it lowers it at young ages. Both changes work to affect mainly the age at which the value of life saving, hence life protection outlays, peak. These predictions are borne out by Figure 4. The projected peak value of life savings changes from \$1.534 million dollars at age 28, to \$1.435 million dollars at age 38, and \$1.523 million dollars at age 55 as r increases from 2.4% to 3.2% and to 4.0%. The impact on life expectancy of the corresponding changes in the pattern of life protection is thus not monotonically related to r, and relatively modest, as shown in Table 2.

B.4 Changes in bequest preferences

By the conditional, closed-form solutions of our model (see equations (A.13)-(A.15)), we expect a **higher** bequest preference to **lower** the propensity for life protection, essentially because placing a higher value on the legacy bequeathed to heirs lowers the risk premium on longevity. Note that our "bequest preference" parameter (n), affects just the utility attached to a financial legacy. Altruism toward surviving dependents, which is not captured by our formal model, may induce greater life protection if one's survival as a household head contributes to the welfare of dependents. Even under our limited bequest preference concept, however, Table 2 indicates that variations in (n) produce only minor changes. A higher n motivates a switch from own lifetime consumption to bequest (life insurance and regular savings), but also a higher asset accumulation over the life cycle in order to support higher desired bequest levels. The optimal values of life saving and life protection spending thus fall only moderately with higher values of n.

B.5 <u>Changes in Wage Income Streams</u>

As already mentioned, reported age-earnings profiles, while capturing the return on healthy time (low morbidity risk) in the labor market, do not capture the full benefits of healthy time as a producer good. One way to account for the latter and its impact on optimal life-and-health protection (assuming that mortality and morbidity risks are monotonically related) is by replacing market earnings by a measure of "full earnings", which incorporates the opportunity cost of healthy time in home production. Since no accurate measures exist, we experiment with implicit full earnings measures that are 25% or 50% higher than observed labor-market earnings.[13]

Higher full earnings that raise human wealth and indirectly non-human wealth accumulation as well increase the incentive to invest in life protection, since the only way to secure future earnings (unlike non-labor income) is through survival. Indeed, life protection and the value of life saving v*(t) increase almost proportionally to W(t). In particular, the peak value of v*(t) rises from $1.435 to $2.141 million as wage income rises 50% from its reported level. Life expectancies become larger as well. At age 18 it increases from the original 59.10 years to 60.89 as the wage income level rises by 50%.

B.6 <u>Exogenous changes in the initial endowment of non-human wealth</u>

In section A we treated the initial endowment of non-human wealth, A(0) as endogenous. Here we allow it to change exogenously. Although equation (A.13) indicates that an exogenous change in A(0) would raise the value of life saving, the increase appears relatively modest in our simulations. When initial wealth increases from \$6315 by 25% or 50%, peak v*(t) rises from \$1.453 to \$1.437 or \$1.439 million dollars at age 38. Note that the effect of a 25% increase in wage income, leading to an approximately equal percentage increase in the value of human wealth at age 18 (L(0)), has a 24.5% larger effect on the value of life saving, and a 25.7% larger effect on life expectancy at age 18, than that of an equal percentage increase in the initial financial endowment. This confirms a key implication of our model about the larger importance of human wealth, relative to human wealth in determining the value of life saving (see section I and Appendix A.2).

B.7 <u>The impact of different health endowments on the demand for life expectancy</u>

It may appear that an improvement in endowed health (a lower biological mortality risk) could lower the demand for life protection (I*(t)), as life expectancy then rises even without additional cost and effort. Our theoretical model indicates, however, that the likely optimal response could be to **raise** life protection. This is because when mortality risks fall, the wealth effect generated by a longer life expectancy increase the value of life saving. Indeed, although the rates of return on actuarial savings (r+f(t)) fall, the non-human wealth accumulation A(t) rises because of greater savings. More important, the capitalized values of human wealth L(t) unambiguously rise because of the reduced mortality risks. Table 2 indicates that both optimal life protection outlays and life expectancy increase as j(t) decreases 25% about its projected age profile.

C. Simulated Extensions of our Model

C.1 <u>Lingering effects of a change in life-protection outlays.</u>

Our theoretical model treats life protection outlays as a flow variable that has no durable impact on age-specific mortality risks. A more general approach would be to allow for such durable effects. A full recognition of durability requires a significant generalization of our model, which we leave for future work. We can use the current framework, however, to assess the qualitative impact of a **discrete change** in the duration of life protection's impact through a simple experiment.

Starting with our imputed baseline "biological" mortality risks, j(t), we study the impact of the exogenous increase in the durability of investment at age 39, I(39), by imposing a symmetrical downward shift in j(t) by 25% over the subsequent 10-year period, since the objective of the experiment is to assess how an implicit change in the durability of **any** life protection outlays affects the entire age-profile of optimal I(t), hence f*(t), and $T^*(t)$. We carry out the simulations under two alternative assumptions: a. the impact of the shift will last for 10 years and then disappear at the end of the 10^{th} year; b. the impact would decay at a constant rate and become zero at the end of the 10^{th} year.

Naturally, an increase in the implicit durability of I(39) raises life-protection's efficacy, hence life expectancy. The main impact of the durability change, however, is shown to be a change in the age-profile of life protection outlays. The lingering impact of I(t) makes it more expedient to invest in it earlier in life because it applies to future as well as current mortality risks, and this incentive is stronger the slower is the rate at which the investment impact depreciates. Higher spending on life protection at younger ages leads to lower mortality rates and higher life expectancy at younger, relative to older age levels. The impact on the value of life saving is similar although the effect is milder the greater is the rate at which the investment benefits depreciate (see Table 3A).

C.2 The impact of social security

Our model ascribes all annuity savings to private annuities. The impact of a pay-as-you-go, defined-benefits social security system can easily be integrated in our simulations by imposing social security taxes at working age levels, and adding the defined social security benefits at retirement ages for our benchmark group. (These simulations still abstract, however, from the impact of Medicare.) Specifically, we impose a 6.2% tax rate on our employee wage-income profile for the benchmark group at all ages, while increasing the annual wage-income levels by $16,614 after age 65, using the "calculator" of the Social Security Administration's web page. This benefit is not subject to the payroll tax while the wage income after age 65 is still subject to the payroll tax. We recomputed the resulting age-earnings profile after applying the 6.2% tax rate to our smoothed earnings profile, as originally calibrated.

Accounting for social security as a distinct "annuity" program produces a significant change in the structure of life protection spending: since social security is a defined-benefits, rather than a defined-contribution scheme, it is shown to create an incentive to postpone spending on life protection to later years, rather than earlier years, which are subject to actuarially unfair taxes. This is reflected by the commensurate change in the structure of $v^*(t)$. Furthermore, the simulations in Table 3B suggest that the existence of social security leads to higher life expectancies at virtually all age level (see Ehrlich, 2000, section VI), although the quantitative impact is modest.

V. APPLICATIONS OF THE BASIC MODEL

We now turn to assess the power of our calibrated simulations to explain observed diversity in age-specific life expectancies across key population groups. The simulations are limited, however, by data available to calibrate group-specific parameters. The reported group-specific data we have are age-earnings profiles by gender, race, and schooling groups. We also have age-specific mortality risks by gender and race. For these groups we explain observed mortality differences by projecting corresponding biological mortality risks and compute to what extent the latter can explain the former. For the specific schooling groups and the population over time we can use only life expectancy data. In these cases we employ our imputed biological mortality risks for our benchmark group to project group-specific life expectancies and compare these to the observed ones.

A. The "Gender Gap" in Life Expectancy

The simulations we use to address the systematic, and persistent, gender gap in age-specific life expectancies, favoring females, are inevitably limited – we apply the same set of parameters used in our baseline case to both sexes, except for mortality rates and wage income profiles. We thus disregard any other possible parametric differences by gender that can induce a relatively higher demand for life protection by females, such as higher risk aversion, or lower opportunity costs of time (our parameter c) for females relative to males of equal schooling and job experience. These omissions inevitably understate the power of life protection to explain the observed gender gap in the following experiment.

The *Vital and Health Statistics of the US (1999), series 2. No. 129 Tables 2 and 3* provide gender-specific mortality rates for 1996. There are no readily available age-earnings profiles by gender for the US population, but the Statistical Abstract of the US provides average wage income by gender, which sets the level of the females' market wage earnings at 58.5% of that of males. In the following simulations (see Table 4) we first derive and smooth out the observed mortality rates for males and females separately, following the methodology described in section II. We then conduct simulations based on alternative assumptions about the true earnings gap by gender.

In the first, we assume that females' wage income is only 58.5% that of males. Females' human wealth, L(t) and value-of-life-saving function, v(t), is thus found to be necessarily lower than that of males. The peak magnitude of value of life saving for females is estimated to be $1.075 million at age 38 while that for males is $1.709 million at age 37. The higher age at which $v^*(t)$ peaks for females reflects essentially their higher survival odds. These estimates imply, in turn, that females undertake less self-protection than males, and their higher life expectancy is due strictly to their lower biological age-specific mortality rates, provided other parameters are equal. Indeed, our separately imputed age profiles of "biological" mortality rates for males and females project even larger gaps between the two relative to the **observed** gaps (e.g., 6.72 vs. 5.83 at age 18).

An alternative assumption is that females' earnings are equal to those of males. The rationale is that females' wage income includes both part-time market earnings and the value of household production, which may approach males' full-time market earnings. In this experiment, females' net human and non-human wealth both become higher than that of males, essentially because of their higher survival odds. The more striking result is that females' value of life saving profile now becomes higher than that of males at virtually all comparable ages, peaking at $1.793 million at age 38. The higher value of $v^*(t)$ for females also means, of course, that they devote more resources to life protection than their male counterparts. This is what our theoretical analysis and the simulations in part IV.B.7 predict, since lower biological mortality risks by themselves raise the demand for life protection (see also EC, 1990). The difference between males' and females' projected "biological" mortality profiles now narrows markedly, which means that life protection accounts for 15.1% of the observed gender gap in life expectancies at age 18 (0.879/5.83). The experiment indicates that females' longer life expectancy may be due **partly** to their lower biological mortality risks, as medical data generally confirms (see, e.g., Bacci, 1965), but **partly** to greater self-protection induced by lower biological mortality risks.[14]

B. Life Expectancy Differences by Race

As was the case for gender, we can objectively distinguish between Caucasians and African Americans (AA) only on the basis of differences in the reported group-specific mortality and wage profiles, using the same data sources we have used to study the gender gap. Average reported earnings for AA is 74.5% that of Caucasians. By assuming that all other parameters are identical, we ignore important "environmental" factors working against effective life protection by AA, such as lower access to medical care (i.e., a higher unit cost of life protection), and higher exposure to risks of murder and injury.

Nevertheless, in this case we are somewhat more successful in explaining the racial differences in life expectancies, favoring Caucasians. In Table 5 we simulate the role of self-protection for both groups by allowing for different "biological" (or "environmental") age-specific mortality rates for each. We then impute the biological rates from the **observed** race-specific mortality age profiles within each group to assess how much of the gap between the two can be ascribed to "biology", or exogenous environmental factors.

The answer we obtain indicates that 23.7% (=1.38/5.82) of the gap in life expectancy across Caucasians and AA can be ascribed to differences in effective life protection due to earnings differences. Note that the omission of environmental differences, such as access to health care, that increase the cost of life protection (c) to African Americans overstates their projected life protection relative to Caucasians. This implies that life protection is even more effective in explaining the observed racial gap in life expectancies.[15]

C. Life Expectancy Gaps Across Schooling brackets

Education, as a measure of human capital affects both efficiency in production of life and health protection, as emphasized in the literature, and the opportunity cost of time in life protection via its influence on the wage rate. Under the "neutrality assumption" invoked in our baseline case, however, education may not affect the relative "unit" cost of life protection, c. Our model suggests, however, a more direct link between education and life expectancy: since the more educated possess relatively higher human wealth, L(t), they will have a higher incentive to protect this wealth through survival. To what extent would this factor alone explain the observed gaps in life expectancy across educational classes?

To answer this question, we impose a common profile of biological mortality rates for males of all educational classes - the j(t) density imputed in our analysis of US males in the preceding section (the emphasis on males is clarified below) - since **no** separate VS data are reported for specific classes. We then consider four education groups: those holding High School, Bachelor, Master, and Doctorate degrees. Wage income profiles for these groups are from the SAUS*, 1998 Table 246, Earnings, by Highest Degree Earned:*

1996.

The results are summarized in Table 6. We start our simulations at age 25, to allow for a reasonable representation of all education groups in the labor market. The simulations indicate that people with more education have a higher human and non-human wealth and thus value of life saving. They also spend more on consumption than others as a result of their greater total wealth. Their non-human wealth profile is thus relatively lower initially, but becomes higher at older age levels. The VLS profile peaks at age 37 for high school graduates and at age 40 for Doctorates. The peak values range from $1.282 million for High School graduates to $3.228 million for Doctorate holders.

Next we project life expectancies for the different education groups by adding to the imputed age-specific biological life expectancies the estimated age-specific impact of life protection. These projections can be compared with life-expectancy estimates for **males** of all races by educational attainments in **1990** in Richards and Barry [RB], (1998, Table 5(a)), linking death certificates data with attained individual schooling. Clearly, our educational categories are not fully comparable with those estimated by RB. Nevertheless, we come close to RB's estimated life expectancies for High School at most ages. Comparing the estimated life expectancy gap between those with High School v. a Bachelor degree in each study, our projected gap explains 47% (=1.43/3) of the actual gap estimated by RB at age 30, 38% at age 38, and 20% at age 55 (the latter two not shown in the table). Our projected life-expectancy gaps between those with High School and a Doctorate degree explain an even larger percentage of the actual gap estimated by RB between those with a High School v. the highest degree (64% at age 30, 51.5% at age 55 and 23.7% at age 55).[16] Our calibrated simulations are thus relatively successful explaining life expectancy differences across education classes.

D. The Trend in Life Expectancy

In our final application, we simulate the time trend of life expectancy for the average wage earner in the economy by calibrating available time-varying parameters backwards from 1996. Again, the only objective data available concern real wage and salary income growth for the representative worker.[17]

The simulation analysis is similar to the one we performed in section IV. We take as a point of reference our recovered "biological" age-specific mortality profile for our baseline case in 1996, j(96), and project the **realized** age-specific life expectancies backwards over the period 1970-1990. We interpolate the shifts in the age-earnings profile based on the rate of growth in average wage income over the same period, as reported in Table P-1, Total CPS Population and Per Capita Money Income: 1967 to 1998, of the U.S. Census Bureau. Our age-specific life expectancy projections are given for 5-year intervals at age 20, to make them comparable to the actually reported age-specific life expectancies, which we take from *National Vital Statistics Report* and various volumes of *Vital Statistics of United States*. The results are summarized in Table 7.

The simulations explain a good portion of the actual changes in life expectancy between 1970 and 1996. For the entire period between 1996 and 1970, our projected growth in the conditional life expectancy at age 20 explains 25.66% (=1.07/4.17) of the actual growth. For the more recent period between 1980 and 1996, our projected growth in life expectancy at age 20 explains 33.33% (=0.57/1.71) of the actual growth in life expectancy. This is not insignificant given that we do not allow for any improvement in medical technology. If we assume that our one-unit cost of life protection fell at the rate of 1% over 1970-1990 as a result of improvement in life saving technologies (which is equal to the growth in the economy's total factor productivity), our simulations would now explain 37.65% of the growth in life expectancy between 1970 and 1996 or 56.73% of the growth between 1980 and 1996. This increased explanatory power reflects the considerable influence of changes in c on predicted life expectancy (see Table 2).

CONCLUSION

The primary contribution of this paper is methodological: our ability to project both the level and diversity in conditional life expectancies and estimates of values of life savings, which our model estimates jointly, as two sides of the same coin. This enables us to assess the relative importance of underlying parameters in determining the impact of life protection on life expectancy and VLS, and to rationalize the observed variability of these variables at different ages, across different population groups, and over time**.**

a. *The quantitative significance of life protection*. These must be viewed with caution because of the simplifications we invoke to specify the model and calibrate the simulations. Nevertheless, our calibrated simulations suggest that, for our benchmark group (the entire US population), average life protection $\bar{I}(t)$ accounts for a reduction of 17.81% in the unobserved average value of "biological" mortality risks $\bar{j}(t)$ between ages 18-77. This impact varies within a range of 4.23% - 9.37% in terms of percentage impact and 2.355 – 5.218 years in terms of absolute impact if we allow for a 25% range of variations in the each of our model's basic parameters separately (see Table 2). Our projected impact of life protection on both mortality risks and remaining life expectancy diminishes as the biological risks rise over the life cycle, but it remains non-negligible at old age as well. Our simulations reveal a much greater influence of human wealth relative to non-human wealth as sources of variations in VLS and in the impact of life protection on life expectancy. This is apparent from Table 2 as well as from Table 6, where large variations in added years of life expectancy are observed across different schooling groups (from 1.825 to 4.839 at age 30). These estimated ranges are little affected if we experiment with alternative assumptions about the durability of life projection efforts or modify our benchmark simulation to account for social security. Our calibrated simulations also reveal the special importance of variations in determinants of the **cost** of life protection in affecting variations in life expectancy. By Tables 2 and 7, variations in the unit cost of our aggregate spending measure of life protection exert a relatively important quantitative impact on inequality in life expectancy across groups and over time.

b. *Diversity across groups*. Our simulations indicate that life protection may also explain a portion of the observed age-specific life expectancy gaps across major population groups. In the case of the 'gender gap', the observed life-expectancy differences favoring females appear to be accounted for either exclusively or primarily by differences in underlying biological endowments, depending on the way we impute the typically greater contribution of females to home production. Life protection seems to be more important, however, in explaining the observed differences in life expectancies across AA and Caucasians (23.7%) at age 18, and low and high schooling classes (51.5%) at age 38. These are arguably conservative assessments, since the only parametric variations we allow across the compared groups are in observed mortality rates and age-earnings profiles (which in turn allow for variations non-human wealth as well).

c. *Evolution over time*. In Table 7 we explain 24%-33.3% of the secular growth in average life expectancy at 20 for different periods away from 1996, triggered just by the secular growth rate of real labor earnings and its impact on real non-human wealth. Assigning a conservative value to the growth in life-saving medical technology, however, is shown to significantly raise these estimates. Based on the same growth rate in real labor earnings (1.58%), we project the actual life expectancy at age 18 to reach 82.04 by the year 2050 (an improvement of 4.94 years).

d. *Diversity in estimated values of life saving*. For the average male in the population our simulated values vary between $0.731 million (age 80) and $1.709 million (age 37). For the educational groupings the range is still wider: $0.572 million for High School Graduates (age 80) and $3.228 million for Doctorates at age 40. Although our estimates of v*(t) are likely to **understate** their level, since they do not account for the consumption benefits of better health (lower morbidity and mortality risk, f(t)), i.e., avoidance of "pain and suffering", which could extend all estimated magnitudes for v*(t) by 25-50%, this range of estimates rationalizes a good part of the variations in empirical estimates of the private value of life saving based regression analyses concerning occupational and consumer groups (see Viscusi (1993)). Our paper offers a theoretical methodology by which variations in VLS across all groups can be rationalized.

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FOOTNOTES

[1] Viscusi and Aldy (2003) also emphasize the importance of recognizing variations in private VLS by age, but do not offer a formal model in this context.

[2] As in deterministic models of health following Grossman (1972) and Ehrlich & Chuma (1990), we do not model education as endogenously determined with life protection. Since our simulations use age 18 or 25 as reference points, however, completed education may be viewed as predetermined. In our simulations we relax somewhat this "Ben-Porath neutrality" assumption by allowing for a range of deviations of c about its "neutral" level.

[3] However, these cross-sectional data do not allow for any adjustments to mortality data due to "cohort effects".

[4] This estimate is based on the assumed cost function of life protection in equation (A.2), setting the parameter $\alpha=2$, and estimates of actual spending on life protection from all sources, discussed below. The actual cost parameter used in the simulations is 3.4×10^8. This parameter implies that the cost of a "one-unit" reduction in I(t), hence in the mortality rate from its biological level (0.01 or 11% of the average fatality rate over the life cycle) is 34,000 dollars.

[5] We have arrived at this figure as follows: after smoothing the reported medical expenditure for different ages (which are quite noisy) over 10-year intervals, we find the average annual medical care spending per person in the age interval 40-49 to be $1703.67 in 1996, which is the year of our sample. The preventive care portion of total spending on each of the categories reported in the MEPS data was then arrived at adding all "primary care", and 50% of all "secondary care", spending totaling $788.22, or 46.27% of total medical care (We are indebted to Dr. Michelle Ehrlich of the Cleveland Clinic for providing these preventive care assessments by categories of care.).

[6] Our Harvey-based lower-bound OSHA annual cost estimate is $300 for 1996. Nachtrieb (2003) bases her figures on NIH studies. The annual "diet" costs, including food supplements, are extrapolated as $173.38 in 1996, and exercise costs are assessed as approximately equal. Adding these spending items to the preventive care figure produces a combined annual estimate of $1,434.98 for life protection spending. The projected total spending on life protection, based on the calibrated simulation for our benchmark group, is quite close: $1,433.32. We do not incorporate time costs involved in specific life protection activities since no reliable estimates exist and our earnings estimate is confined to market earnings.

[7] Theoretically, our model allows for variations in n(t) over the life cycle. While preference for bequest may change in accordance with the individual's marital or family status, any assumed changes in the life-cycle pattern of n(t) would be rather speculative in the context of the present formulation, justifying our setting n to be constant.

[8] This figure is a conservative estimate of the real return on a total portfolio consisting of

50% treasury bills, 25% government bonds, and 25% S&P 500 stocks over the 50-year period preceding 1996 where the corresponding yields were 1.33%, 2.14%, and 8.08%. Davies (1981) is using a similar real rate of return estimate.

9 SAUS data for 1995 and 1998 imply that the median non-human wealth of a 65 years old family head is $343,197 in 1996 (using the annual growth rate of 14.09% for median wealth between 1995 and 1998). This produces a **mean** value of $473K on the assumption that wealth, like earnings, is log-normally distributed with a median of $343K and a dispersion value of 0.8 (derived via a grid search that produces comparable values of the mean and the standard deviation of the wealth distribution.) In 1996 we also project the "social security wealth" of an average family head to be $175,698 at age 65. This estimate is obtained by discounting the annual benefit stream of $16,614 for a 65 years old recipient over the following 12 years (i.e., through life expectancy) at the reported 2% yield on social security taxes. The total mean wealth level thus computed is $659K, which is comparable to our model's projection. Our projected mean wealth and social security wealth at age 65 are quite close: $694.92 and $165.79K (see section IV.C.2). They are also close to those in Mitchell (2001), $625K and 174K, respectively.

10 Thaler and Rosen (1976) report just a weak and insignificant age effect on their regression estimate of VLS based on wage regressions, presumably because the interaction term they use to capture the age effect "linearizes" the upward rising, flat and declining shape of VLS we simulate in figure 4.

11 Note that the relationship between survival risks and life expectancy is non-linear. The latter is less than proportionally related to the former. This is due partly to the fixed planning horizon D.

12 Since the value of c has been calibrated based on the personal outlays on preventive life protection (see section II), C, and an assumed value of α, when we vary α in this experiment, we also reconfigure the calibrated value of c to make the comparison relevant.

13 For age groups beyond 80, where we do not have reported market earnings, we maintain the same 25% and 50% increments applied to the reported earnings at age 80.

14 We also ran simulations imposing on both sexes the "biological" mortality density function j(t) we imputed in Table 1 for the total population. Using the reported earnings profile for females (58.5% that of males), we then project a higher life expectancy levels for males than for females at all ages. This experiment thus contradicts the possibility that the sexes have identical j(t) functions, consistently with the simulations in Table 4.

15 As in the case of gender, we also ran simulations imposing the general population's "biological" or environmental mortality density functions on both racial groups j(t). Here the results were more consistent with those reported in Table 5. They imply that 15.8% of the observed disparity in life expectancies across the two groups can be ascribed to

differences in life protection, as opposed to "environment". Both experiments suggest that the value of life saving measure for AA is 71% - 75% of that of Caucasians at their peak.

[16] To the extent that persons with higher schooling are self-selected by virtue of their higher (endowed) survival probabilities, our assumed common j(t) density for all schooling groups understates our projected life expectancies especially for those with higher educational attainments.

[17] Note, however, that the equilibrium value of initial non-human wealth is an endogenous variable in all our calibrated simulations, since we project its magnitude based on the expected bequest level of a representative parent one generation apart.

APPENDIX A

1. Model specification

The formal model follows Ehrlich (2000, section 5). The stochastic probability law governing the 'force of mortality', the definitions of the control and state variables, and the utility, 'self-protection' production, and cost functions are discussed in the text. The maximized expected utility function in this formulation is:

$$(A.1)\; J_t(A(t),t;\alpha') = Max_{Z,B,I}\; E\{\int_t^{\tilde{D}} \exp[-\rho(s-t)]U(Z(s))\,ds + \exp[-\rho(\tilde{D}-t)V(B(\tilde{D}),t)]\}$$

where $\tilde{D}$ denotes the stochastic time of death, ρ an inter-temporal discount factor, and α' a parameter vector, subject to wealth constraints:

$$(A.2)\; \overset{0}{A}(t) = (r+f(t))A(t) + w(t)h(t) - cI^{\alpha}(t) - Z(t) - f(t)B(t),$$

$$(A.3)\; 0 \le B(t) \le A(t) + L(t) \ge 0,$$

and boundary conditions:

$$(A.4)\; J(A(D),D;\alpha') = V(B^*(D),D) = V(A(D),D) \text{ and } A(D) \ge 0.$$

In equation (A.2)-(A.4), A(t) denotes the current value of non-human wealth,

$$(A.2a)\; A(t) = \exp(rt + m(0,t))\;\{A(0) + \int_0^t \exp(-ru - m(0,u))[wh(u) - cI^{\alpha}(u) - Z(u) - f(t)B(t)]du\},$$

where $m(0,u) = \int_0^u f(s)ds$, w(t) = the wage rate, h(u) = healthy (labor) time, L(t) = net human wealth, i.e.,

$$(A.3a)\; L(t) = \int_t^D \exp[-r(u-t)-m(t,u)][w(u)h(u) - cI^{\alpha}(t)]du, \text{ where } m(t,u) \equiv \int_t^u f(s)ds,$$

and D denotes the terminal date of the planning horizon that must be used to solve our stochastic dynamic program. Its determination is discussed in section IV.C in the text.

By the stochastic dynamic programming approach, the solution must satisfy

(A.5) $-J_t = -\rho J + U(Z^*) + J_A[(r+f)A + w(t)h(t) - cI^{\alpha}(t) - Z^* - fB^*] + f[V(B^*,t) - J]$,

where $J_t \equiv \partial J(A(t),t;\alpha')/\partial t$.

The optimal control variables I^*, Z^*, and B^* are then solved from

(A.6) $[\alpha cI(t)^{\alpha-1}]^* = (1/J_A)[J(A(t),t;\alpha) - V(B^*)] + B^* - A \equiv v^*(t)$

(A.7) $U_Z(Z^*) = J_A$

(A.8) $B^* = \quad 0$ if $J_A > V'(B^*)$

$\quad \epsilon\ (0, A(t)+L(t))$, if $J_A = V'(B^*)$

$\quad A(t)+L(t)$, if $J_A < V'(B^*)$.

2. Conditional Explicit Solutions

No explicit solutions can be obtained for the system (A.6)-(A.8). To obtain a conditional closed-form solution for the maximized life-time expected utility function J_1 in equation (A.1), the instantaneous utility of consumption function is first specialized to exhibit 'constant relative risk aversion',

(A.9) $U(Z) = (1/k)Z^k$,

where $0 < k < 1$ to assure concavity, and $d = (1-k)$ denotes the degree of relative risk aversion. The utility of bequest function is similarly specialized as

(A.10) $V(B,t) = [n(t)/k]B^k$,

with n(t) representing the intensity of utility derived by the individual from capital to be bequeathed to heirs. Finally, the optimal consumption and bequest choices are now taken to be conditional on a **predetermined** path of optimal self-protection outlays.

These simplifications permit an explicit solution for the partial differential equation (A.5), conditional on an optimal path of self-protection inputs (I), i.e., taking the age-specific density of mortality rates f(t) as given.. The solution can be shown equal to

(A.11) $J(A(t),t;\alpha) = [a(t)/k][A(t) + L(t)]^k$.

where a(t) represents the marginal expected utility of a unit of wealth while one is alive. It s solution is given by

$$(A.12)\ [a(t)]^{(1/d)} = \exp\{-\int_t^D x(u)du\}\,[n(D)]^{(1/d)} + \int_t^D y(u)\exp\{-\int_t^u x(s)ds\}du,$$

where $x(u) \equiv f(u) + [(\rho\text{-}rk)/(1\text{-}k)]$, and $y(u) \equiv 1+f(u)[n(u)]^{(1/d)}$.

Equations (A.11) and (A.12) provide an explicit solution for the indirect expected utility of the remaining life span, **conditional** on optimal self-protection inputs (I*(t)). By exploiting equations (A.6), (A.7), (A.8), and (A.11), we can obtain similarly conditional explicit solutions for the co-state variable $v_1^*(t)$, or the value-of-life-saving function, and the optimal values of consumption and bequest as follows:

(A.13) $v^*(t) = (1/k)L(t)+[(1-k)/k][A(t)-B^*(t)] = z(t)[A(t) + L(t)] - A(t)$

where $z(t) = [n(t)/a(t)]^{(1/d)} + (1/k)\{1-[n(t)/a(t)]^{(1/d)}\}$,

(A.14) $Z^*(t) = [1/a(t)]^{(1/d)}[A(t) + L(t)]$, and

(A.15) $B^*(t) = [n(t)/a(t)]^{(1/d)}[A(t) + L(t)]$.

Equation (A.13) indicates the greater importance of human (L(t)), relative to non-human (A(t)) wealth in affecting the value of life saving. For a detailed interpretation of this result see Ehrlich (op. cit.).

3. **Unconditional Solutions**

Using the explicit solutions (A.13)–(A.15) and the first order condition for the optimal self-protection (A.6), an unconditional solution to all three control variables of the model, and thus for the model's co-state and state variables as well, can be found through the iterative procedure described in the text and in Appendix B.

APPENDIX B

The iteration procedure we use is similar to Newton's method, except that we do not use the system's Jacobian matrix to enhance the convergence speed. It involves the following steps:

- Step A: Initialize a path of life-protection efforts, I(t). In the benchmark case proceed to step B. In our calibrated simulations we use the initialized I(t) to construct f(t) from previously projected j(t) and then proceed to obtain $m(i,j) \equiv \int_i^j f(t)dt$ through numerical integration.
- Step B: Calculate by numerical integration the factor a(t) – a component of the intensity of the optimal value function (A.11) – using its definition in eq. (A.12) of Appendix A. This calculation is done on the basis of the computed values of f(t) and m(i,j), and subject to our calibrated values for the other basic parameters of the model: the real rate of interest, r, the rate of time preference, ρ, the intensity of bequest preference, n, and the degree of relative risk aversion, 1-k.
- Step C: Calculate financial wealth A(t), bequest B(t), consumption Z(t), and net human wealth L(t) (the discounted labor income net of the cost of self-protection) as follows:

  C1: Given I(t) and f(t), calculate L(t) by numerical integration using equation (A.3a) in Appendix A.

  C2: Calculate Z(t) and B(t). As in Ehrlich (2000) equation (3.7a), Z(t) has a growth rate of (r-ρ)/(1-k), and from (A.14), Z(0) can be determined by A(0), a(0), and L(0). B(t) can be similarly calculated, given the assumed value of the intensity of bequest preferences , since by equations (A.14) and (A.15) $B(t) = n(t)^{1/(1-k)} Z(t)$.

  C3: Given the solutions to Z(t), L(t) and a(t), we can use (A.14) to solve for A(t).
- Step D: Calculate the value of life saving v*(t), thus life-protection expenditures I(t), as given in equation (A.13), using A(t), B(t), and L(t) from the previous step.
- Step E: Compare I(t), as calculated in Step D, with the preceding path of I(t). (In the first round, the "preceding path" is the initialized path). Define diff = $\text{Max}_t\, [|I(t) - I^0(t)| / I^0(t)]$, where $I^0(t)$ is the preceding path of I(t), i.e., diff is the maximum percentage change in I(t). If diff < tol, where tol is some pre-specified tolerance level, the system converges, and you may report the results. If diff > tol, record the current new I(t) as the previous path of I(t) and proceed to Step C. The tolerance level we have chosen for tol is 10^{-5}.

Table 1: Calibrated Simulations of Life-Protection Choices in our Baseline Case (1996 data) Conditional on survival to:

Age 18	Peak of v*(t)		Age 65	Actual Life Expectancy at 18	
	Age	Value		Age	Value
1a. Remaining Actual Life Expectancy $T^*(t)^{\#}$					
59.08			17.58		
1b. Net Human Wealth L(t) (in $K)*					
610.27	38	653.52	234.21	77	43.37
1c. Non-Human Wealth A(t) (in $K)*					
6.50	38	172.80	694.92	77	793.41
1d. Value of Life Saving v(t) (in $M)*					
1.191	38	1.435	1.090	77	0.775
1e. Expenditure on Life Protection C(t) (in $)					
1043.1	38	1514.1	873.1	77	441.9
1f. Observed Mortality Risks f(t)					
0.0009	38	0.0019	0.0166	77	0.0445
1g. Imputed "Biological" Mortality Risks j(t)					
0.0026	38	0.0040	0.0182	77	0.0457
1h. Impact of Life Protection on "Biological" Life Expectancy (years)					
3.426	38	1.614	0.249	77	0.065
1i. Impact of Life Protection on "Biological" Life Expectancy (%)					
6.155	38	4.172	1.435	77	0.656

Basic parameter set: k = 0.5, r = 3.2%, ρ = 1.5%, n = 1.2, α=2, and c = 3.4.

* Life Expectancy T*(t), the actuarially fair values of net human wealth L(t), non-human wealth A(t), and value of life saving v(t) are defined in Appendix A.

Remaining actual life expectancy for the benchmark group.

Table 2: Life Protection's Impact on Life Expectancy and Value of Life Saving
Role of Parameter Changes

Parameter	Range	Impact on Life Expectancy at 18		Value of Life Saving at	
		Percentage	Years	Peak Age	Peak Value
k	0.375	7.939	4.419	38	1.823
	0.5*	6.155	3.426	38	1.435
	0.625	5.060	2.817	38	1.186
c	2.55	8.300	4.621	38	1.432
	3.4*	6.155	3.426	38	1.435
	4.25	4.890	2.722	38	1.437
α	1.5	4.230	2.355	38	1.424
	2.0*	6.155	3.426	38	1.435
	2.5	8.015	4.462	38	1.448
r	2.4%	6.242	3.475	28	1.534
	3.2%*	6.155	3.426	38	1.435
	4.0%	6.302	3.508	55	1.523
n	0.9	6.174	3.437	38	1.439
	1.2*	6.155	3.426	38	1.435
	1.5	6.131	3.413	37	1.430
W(t)**	$26,658*	6.155	3.426	38	1.435
	+25%	7.750	4.314	38	1.789
	+50%	9.373	5.218	38	2.141
A(0)***	$6,315#	6.155	3.426	38	1.435
	+25%	6.163	3.431	38	1.437
	+50%	6.172	3.436	38	1.439
j(t)	-25%	6.691	3.966	39	1.485
	Original*	6.155	3.426	38	1.435
	+25%	5.707	3.003	37	1.391

* Denotes our selected benchmark parameter and initial conditions.
** Upward adjustments of 25% and 50% are meant to capture alternative "full earnings" levels, adjusted for home production.
*** Upward adjustments designed to be comparable to those for W(t).
[#] A(0) in the benchmark case is imputed from the bequest choices of the previous generation (see text).

Table 3: Calibrated Simulations of Life-time Choices in our Benchmark Case
Additional Sensitivity Analysis

At Age:	18	Peak of $v_1(t)$		65	Life Expectancy at 18	
Change		Age	Value of		Age	Value of
A. Allowing I(39) to have a lingering effect on j(t) over ages 40-50						
3A.1 Remaining Projected Life Expectancy						
0*	59.08			17.58		
-25%	59.44			17.58		
-25%(10%)#	59.27			17.58		
+25%	58.72			17.58		
+25%(10%)#	58.88			17.58		
3A.2 Value of Life Saving (in million dollars)						
0*	1.191	38	1.435	1.090	77	0.775
-25%	1.197	38	1.448	1.088	78	0.743
-25% (10%)#	1.194	38	1.442	1.089	77	0.774
+25%	1.185	37	1.423	1.092	77	0.777
+25%(10%)#	1.188	38	1.428	1.091	77	0.776
3A.3 Expenditure on Life Protection						
0*	1043.1	38	1514.1	873.1	77	441.9
-25%	1053.3	38	1540.7	870.2	78	405.8
-25%(10%)#	1048.9	38	1529.0	871.7	77	441.0
+25%	1033.0	37	1488.1	876.1	77	443.7
+25%(10%)#	1037.3	38	1499.4	874.5	77	442.7
B. Recognizing Social Security						
3B.1 Projected Remaining Life Expectancy						
Unadjusted*	59.10			17.58		
Adjusted**	59.14			17.60		
3B.2 Value of Life Saving (in million dollars)						
Unadjusted*	1.191	38	1.435	1.090	77	0.775
Adjusted**	1.173	40	1.442	1.228	77	0.805
3B.3 Expenditure on Life Protection						
Unadjusted*	1043.1	38	1514.1	873.1	77	441.9
Adjusted**	1011.4	40	1528.8	1109.1	77	477.0

Basic parameter set: $r = 3.2\%$, $\rho = 1.5\%$, $n = 1.2$, and $c = 3.4$.

Assuming a straight-line depreciation of the durability impact

* Note: the simulated values for our benchmark case in Table 1 are the same as the actual

** Simulations adjusted after imposing social security taxes and benefits

Table 4: Calibrated Simulations of Lifetime Choices by Gender (1996 data) Using Alternative Earnings Estimates

At Age:	18	Peak of $v_1(t)$		65	Life Expectancy at 18	
Sex		Age	Value of		Age	Value of
4a. Remaining Actual Life Expectancy						
Male	56.09			15.75		
Female[1]	61.92			19.04		
4b. Value of Life Saving (in $M)						
Male	1.435	37	1.709	1.227	74	0.947
Female[1]	0.893	38	1.075	0.823	80	0.508
Female[2]	1.486	38	1.793	1.371	80	0.842
4c. Observed Mortality Risks f(t)						
Male	0.0012	36	0.0024	0.0213	74	0.0452
Female[1]	0.0005	38	0.0012	0.0126	80	0.0489
4d. Imputed "Biological" Mortality Risks j(t)						
Male	0.0033	37	0.0050	0.0231	74	0.0466
Female[1]	0.0018	38	0.0028	0.0138	80	0.0497
Female[2]	0.0027	38	0.0039	0.0146	80	0.0502
4e. Impact of Life Protection on Life Expectancy (years)						
Male	3.683	37	1.755	0.224	74	0.078
Female[1]	2.789	38	1.325	0.203	80	0.031
Female[2]	4.562	38	2.185	0.341	80	0.054
4f. Impact of Life Protection on Life Expectancy (%)						
Male	7.028	37	4.762	1.441	74	0.765
Female[1]	4.716	38	3.206	1.078	80	0.342
Female[2]	7.953	38	5.399	1.825	80	0.606

*Basic parameter set: r = 3.2%, k = 0.5, ρ = 1.5%, n = 1.2, α=2, and c = 3.4.

[1] SAUS reported average female labor earnings equal 58.4% of male earnings.

[2] Female "full-time" earnings equated with reported male labor earnings.

Table 5: Calibrated Simulations of Lifetime Choices by Race (1996 data)

At Age:	18	Peak of $v_1(t)$		65	Life Expectancy at 18	
Racial group		Age	Value of		Age	Value of
5a. Remaining Actual Life Expectancy						
Caucasian	59.65			17.68		
Af. American	53.83			15.87		
5b. Value of Life Saving (in $M)						
Caucasian	1.230	37	1.475	1.099	78	0.740
Af. American	0.885	36	1.043	0.788	72	0.671
5c. Observed Mortality Risks f(t)						
Caucasian	0.0008	37	0.0016	0.0160	78	0.0482
Af. American	0.0013	36	0.0035	0.0244	72	0.0432
5d. Imputed "Biological" Mortality Risks j(t)						
Caucasian	0.0026	37	0.0037	0.0177	78	0.0493
Af. American	0.0026	36	0.0051	0.0256	72	0.0442
5e. Impact of Life Protection on Life Expectancy (years)						
Caucasian	3.554	37	1.743	0.245	78	0.053
Af. American	2.174	36	1.087	0.154	72	0.078
5f. Impact of Life Protection on Life Expectancy (%)						
Caucasian	6.335	37	4.369	1.404	78	0.561
Af. American	4.210	36	2.972	0.982	72	0.663

Basic parameter set: r = 3.2%, k = 0.5, ρ = 1.5%, n = 1.2, α=2, and c = 3.4.

SAUS reported average black labor earnings equal 74.5% of white earnings.

Table 6: Calibrated Simulations of Lifetime Choices by Education (1996 data), Using Imputed Biological Mortalities of Benchmark Group*

At Age:	30	Peak of $v_1(t)$		65	Life Expectancy at 25	
Education		Age	Value of		Age	Value of
6a. Remaining Projected Life Expectancy using Benchmark Biological Risks**						
High School	44.41			15.71		
Bachelor	45.84			15.84		
Master	46.51			15.91		
Doctorate	47.42			15.99		
6b. Value of Life Saving (in $M)						
High School	1.256	37	1.282	0.955	74	0.911
Bachelor	2.183	38	2.245	1.651	76	1.485
Master	2.651	36	2.689	1.984	76	1.801
Doctorate	3.098	40	3.228	2.485	78	2.113
6c. Impact of Life Protection on Life Expectancy (years)						
High School	1.825	37	1.335	0.180	74	0.146
Bachelor	3.256	38	2.258	0.311	76	0.203
Master	3.932	36	2.998	0.379	76	0.249
Doctorate	4.839	40	3.041	0.467	78	0.239
6d. Impact of Life Protection on Life Expectancy (%)						
High School	4.286	37	3.621	1.158	74	1.027
Bachelor	7.646	38	6.265	2.001	76	1.559
Master	9.235	36	7.956	2.441	76	1.910
Doctorate	11.364	40	8.835	3.007	78	2.015
6e. Estimated Remaining Life Expectancies Based on Death Certificates Data (RB 1990)**						
High School	44.4			15.5		
Some College	44.9			15.6		
Bachelor	47.4			16.6		
More Than Bachelor	49.1			17.9		

* See notes to Table 1. Benchmark group here is the males group in Table 5.

** Estimated life expectancies in BR, thus in our simulations are for males.

Table 7. Trends in Life Expectancy at Age 20* (through 1996)

	Year				
	1970	1975	1980	1985	1990
Remaining Life Expectancy					
Projected[1]	56.10	56.35	56.60	56.82	57.04
Projected[2]	55.60	55.89	56.20	56.51	56.86
Actual	53.00	53.9	55.46	56.1	56.63
Increase in Life Expectancy from Selected Year to 1996					
Projected[1]	1.07	0.82	0.57	0.35	0.13
Projected[2]	1.57	1.28	0.97	0.66	0.31
Actual	4.17	3.27	1.71	1.07	0.54
Percentage Explained					
Projected[1]	25.66	25.08	33.33	32.71	24.07
Projected[2]	37.65	39.14	56.73	61.68	57.41

* Backward projections based on imputed "biological" mortality rates in 1996. Projections shown at age 20, to make them comparable to actually reported age-specific life expectancies in VS publications. The Basic parameter set is the same as in Table 1.

[1] Based on reported labor earnings for the general population.

[2] Based on a 1% annual rate of reduction in real c (same as economy-wide TFP growth).

Figure 1: Calibrated Simulations in Benchmark Case: Maximized Expected Utility

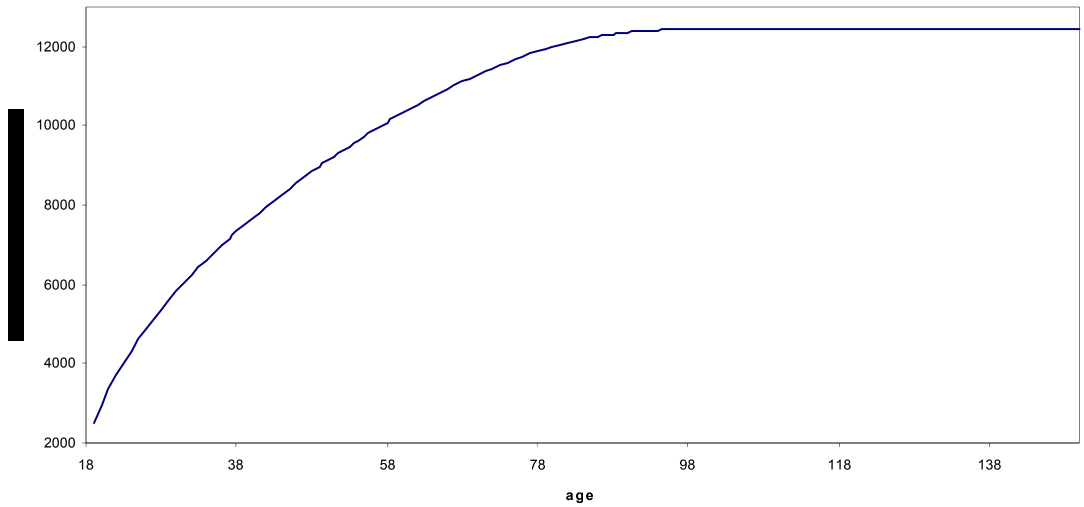

Figure 2: Calibrated Simulations of Benchmark Case: Net Human Wealth

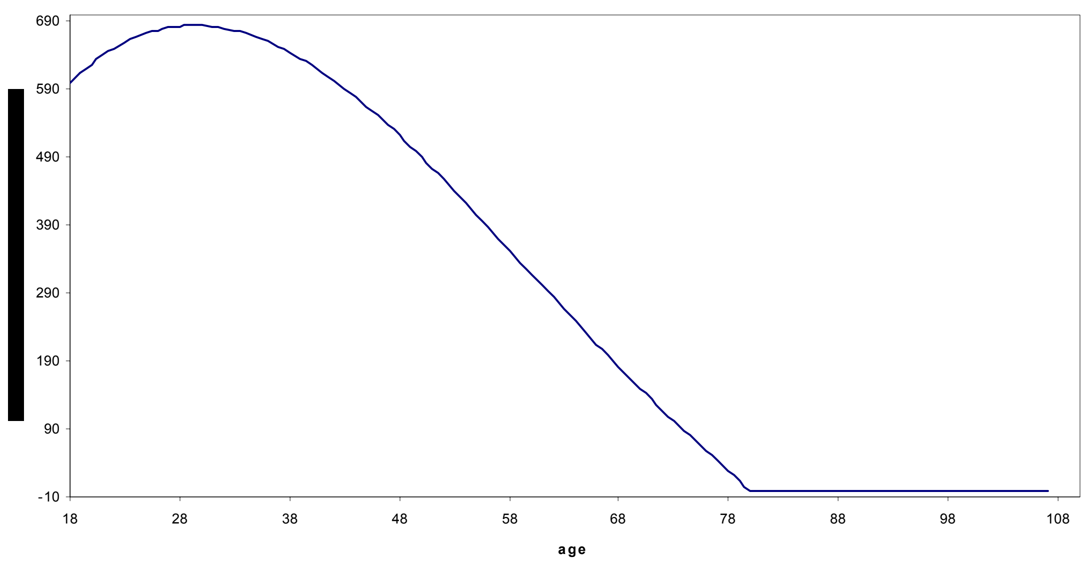

Figure 3: Calibrated Simulations of Benchmark Case: Non-Human Wealth

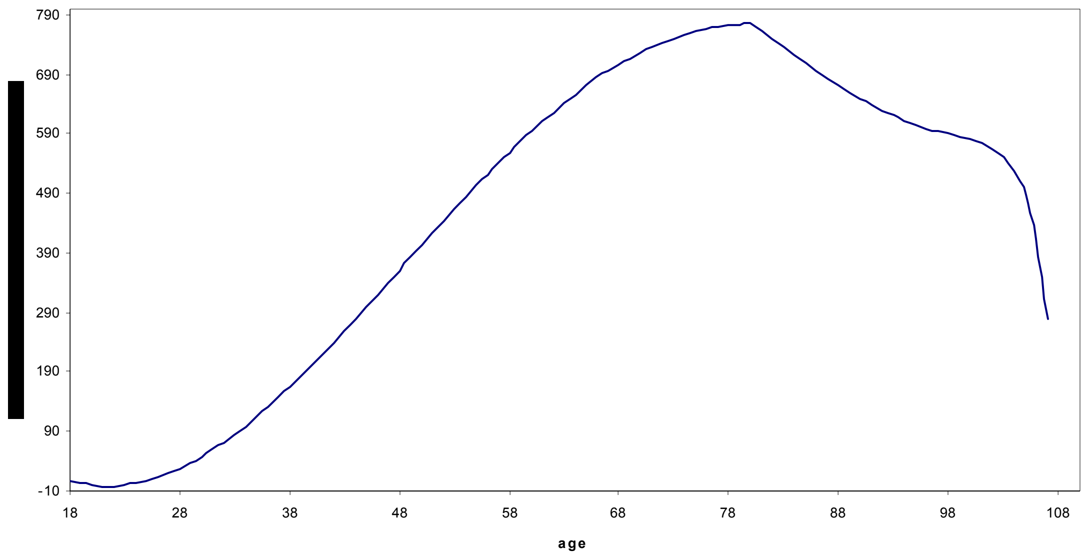

Figure 4: Calibrated Simulations (using Alternative Interest Rates): Value of Life Saving

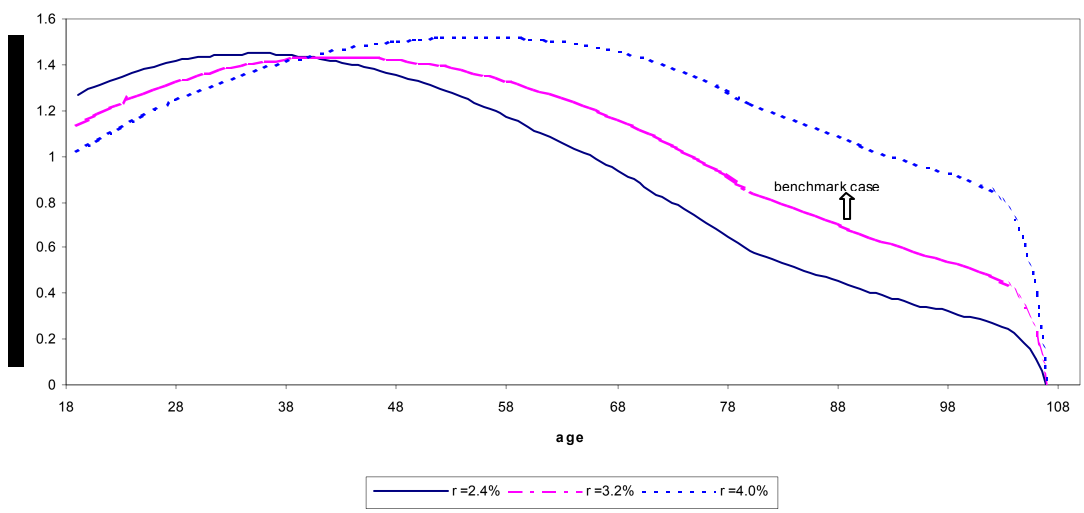

Figure 5: Calibrated Simulations of Benchmark Case: "Biological" v. Observed Mortality Rates

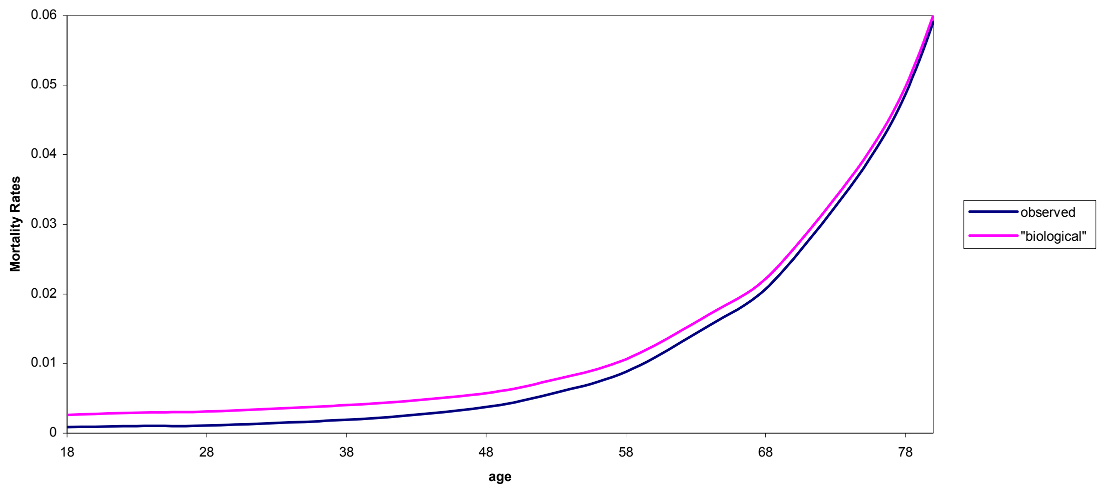

Figure 6: Calibrated Simulations of Benchmark Case: Life Expectancy based on "Biological" v. Observed Mortality Rates