

Accounting for the Rise of Health Spending and Longevity*

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Abstract

We estimate a stochastic life-cycle model of endogenous health spending, asset accumulation and retirement to investigate the causes behind the increase in health spending and longevity in the U.S. over the period 1965-2005. We estimate that technological change and the increase in the generosity of health insurance on their own may explain 36% of the rise in health spending (technology 30% and insurance 6%), while income explains only 4% and other health trends 0.5%. By simultaneously occurring over this period, these changes may have led to complementarity effects which we find to explain an additional 57% increase in health spending. The estimates suggest that the elasticity of health spending with respect to changes in both income and insurance is larger with co-occurring improvements in technology. Technological change, taking the form of increased health care productivity at an annual rate of 1.3%, explains almost all of the rise in life expectancy at age 25 over this period, while changes in insurance and income together explain less than 10%. Welfare gains are substantial and most of the gain appears to be due to technological change. Because of the importance of complementarities, the model is able to reproduce the widening of the income-mortality gradient and in particular the fact that improvements in mortality appear to be mostly concentrated in the top-half of the income distribution.

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1 Introduction

The growth of health spending is a constant preoccupation of policy makers around the world. In the United States, real per capita personal health care spending in 2005 was 10 times what it was in 1965 (in constant dollars \$5,738 vs. \$570). As a fraction of per capita GDP, health spending in the U.S. has grown from 4% to 16%.

What accounts for this rise? The usual suspects are income growth, the spread of health insurance and its generosity and, finally, technological progress in health care (Newhouse, 1992). A simple accounting exercise using back-of-the-envelope calculations shows that income and insurance fall short of explaining the rise and thus that technology must play a role. Evidence on the long-run income elasticity of health spending suggests that it is close to 1 (Gerdtham and Jonsson, 2000), and per capita GDP in 2005 was 4 times that of 1965. Hence, income growth would account for at most 40% of the 10-fold increase in health spending. Similarly, insurance coverage and generosity both expanded over the period. In 1965, consumers paid for 53% of personal health care expenditures, compared to less than 20% in 2005, according to aggregate National Health Expenditure Accounts. The RAND Health Insurance Experiment suggest a price elasticity of -0.2 to -0.3 for medical spending (Manning et al., 1987). Hence, insurance growth would explain roughly 12-18% of the growth in spending. Taken together, income and insurance generated approximately half of the growth. According to Newhouse (1992), the other half must be due to technology.¹

Indeed, technology may also have significantly improved longevity. In 2005, a new-born male could expect to live 7.3 additional years, according to figures from the Human Mortality Database (77.7 in 2005, compared to 70.4 in 1965). Most of that rise is due to lower mortality rates at older ages as the increase in remaining life expectancy at age 50 is 5.8 years. There is plenty of evidence that technological innovation has saved lives. Cutler et al. (2006a) suggest that 70% of the decline in mortality rates can be attributed to declining mortality from cardio-vascular risk, an area where technological innovation has drastically changed the

¹Newhouse (1992) also reviews other explanations such as aging, factor productivity (price) and supply induced-demand.

way patients are treated. Skinner and Staiger (2009) investigate the evolution of survival across hospitals with different levels of technology for treating heart attacks and show that the largest gains were observed in hospitals where diffusion of technology, measured by the use of new and more efficient treatments, was the fastest. Cutler et al. (2006b) argue that technological change is the leading explanation for the increase in longevity witnessed after 1950.

Gains in income do not appear to play a major role. For example, income variation in adult life at the micro-level does not appear to lead to differences in health outcomes (Adams et al., 2003; Smith, 2007) and the RAND Health Insurance Experiment in the 1970s showed that, for the most part, increased insurance coverage did not improve health outcomes in the non-Medicare population (Manning et al., 1987).

Technological progress may therefore bring about both higher spending and longevity. But preferences must be consistent with higher spending when technology improves (Hall and Jones, 2007). New treatments can be more costly than older ones but yield better health outcomes, in which case health spending will increase if individuals accept to pay the additional cost. This will depend on preferences. Newer technologies can also be less costly and more productive than older ones, leading to both cost savings and improved health outcomes. Still, even less costly technologies might increase spending as a result of two important effects. First, they may allow new subgroups of patients to be treated effectively, perhaps as a result of the inability of older treatments to do so, leading to more people being treated. Cutler and McClellan (2001) argue that treatment expansion is an important channel through which technological change may have led to more spending. Second, new treatments for one disease may raise the value of health investments for the population that does not have the disease due to the complementarity in health investments. For example, finding a cure for cancer increases the value of health investments for individuals currently without cancer because it increases their life expectancy, and thus the length of time over which they can reap benefits from their investments. Murphy and Topel (2006) argue that this type of complementarity may be important for understanding the social

value of technological progress in health care.

Hall and Jones (2007) build a model of the U.S. economy where agents optimally allocate resources between health and consumption. They show that preferences alone can generate a rise of the income share devoted to health if the marginal utility of consumption declines faster than the marginal product of health spending as income rises. But for income alone to explain the same rise without help from technology, the income elasticity of health spending must be above 3, which is at odds with empirical evidence (Acemoglu et al., 2013; Gerdtham and Jonsson, 2000).

In this paper, we analyze the growth of health care spending using an estimated life-cycle model that is consistent with empirical elasticity estimates. In our model agents make consumption, health investment, saving and labor-supply decisions in a rich environment that includes several sources of uncertainty and many of the institutions faced by agents over the life-cycle, such as Social Security, taxation and health insurance. This framework allows us to integrate in a single model the determinants of both health spending and health/longevity, and to perform counterfactual simulations that allow for welfare comparisons. We use longitudinal micro data from the Panel Study of Income Dynamics (PSID) and the Medical Expenditure Panel Study (MEPS) to estimate parameters of the model. Preference and technology parameter estimates are then used to perform counterfactual simulations. The estimates imply that health spending is relatively inelastic to income and price (co-insurance rates), with elasticities of 0.6 and -0.5, respectively, prior to age 50. We calibrate productivity growth and mortality trends due to other factors such that we match the 1965 to 2005 experience in terms of health spending and longevity. The counterfactual simulations show that income, insurance and technology are complements in explaining the rise of health spending and longevity. The important implication of this result is that technology per se is not responsible for the rise in health spending. Holding constant the economic resources available in 1965, agents would not have increased by much the share of resources spent on health as a result of new technology becoming available. Only as resources grew, health insurance coverage expanded, and new productive treatments were becoming available, did

the demand for health care grow as much as it did. We also investigate the welfare implications of these changes using compensating variation in expected utility and find that the 2005 economic, health and technological environment, when compared to the environment in 1965, is worth to agents as much as 76% of their 2005 consumption. Although this estimate may appear to be large, we show that it is consistent with common estimates of the value of life extension. Finally, because the model allows disaggregation by income groups, we investigate how the distribution of mortality across income groups has shifted over the period and find that the predictions are consistent with observed patterns.

A number of recent papers also feature endogenous health investments. These models differ in important respects from ours, in particular in formulation, methods employed, and research questions investigated. DeNardi, French and Jones (2010) assume survival is exogenous to health investments. In order to simultaneously model health spending and survival, our model explicitly endogenizes the effect of health spending on survival. On the other hand, macro models such as Suen (2005) are calibrated and focus on representative agents. Instead, we estimate preferences and technology which allows us to quantify the sources of growth in spending and longevity. Furthermore, we allow for a rich environment which features detailed Social Security rules along with a retirement decision. Allowing for retirement may be important as it is another margin of adjustments for agents (Galama et al., 2013).²

The rest of the paper is structured as follows. In section 2, we illustrate how income growth and technological improvements can be complements when it comes to explaining the rise of health spending. In section 3, we present the richer model, which we estimate in section 4 on micro-data. In section 5, we perform counterfactual simulations. Section 6

²Other papers are more distantly related to ours. Blau and Gilleskie (2008) consider a model of retirement choices where health investments are modeled using doctor visits. They focus on understanding the role of changes in health insurance on employment of older males. Their model does not include savings nor endogenous longevity. Halliday, He and Zhang (2009) assume survival is exogenous to health investments. Yogo (2009) and Hugonnier et al. (2013) consider the problem of portfolio choice and health spending after retirement. Khwaja (2010) estimates the willingness to pay, or the value to the individual, of Medicare, developing a model for the demand for health insurance over the life-cycle. Scholz and Seshadri (2010) estimate a model of retirement and health expenditures and focus on the age 50+ population. They examine the effect of Medicare on patterns of wealth and mortality.

concludes.

2 Stylized Model

To illustrate how different sources of growth interact, we revisit the stylized model in Hall and Jones (2007). The agent receives a constant annual income y over his life-cycle and chooses how to allocate his income between consumption and medical expenditures. His life expectancy, L , depends on how much he spends annually on health, m . The production function relating medical expenditures to length of life is concave in m and given by $L(z, m)$, where z is a technology parameter. The agent derives utility from consumption c , where the utility function $u(c)$ is concave in c . He faces the budget constraint $y = c + m$. His lifetime utility is simply the product of length of life and the utility he gets each year.³

The agent's problem is to maximize

$$v(m, z, y) = L(z, m)u(y - m)$$

Hence, define

$$V(z, y) = \max_m v(m, z, y)$$

where $V(z, y)$ represents the maximum lifetime utility that can be attained for a given z and y . The solution to this problem is a demand for health function, $m^*(z, y)$. Define $\eta_L(m) = mL_m(z, m)/L(z, m)$ to be the elasticity of the life expectancy function with respect to health care spending, and $\eta_u(c) = cu_c(c)/u(c)$ to be the elasticity of utility with respect

³This simple result emerges in a life cycle model with constant income and a rate of return equal to the subjective time preference rate. Since productivity of medical expenditures does not depend on age and declines with spending, the consumer will also spend a constant amount on health each year. Hence, the dynamic formulation simplifies to a static two-goods model with the objective function being the product of per-period utility times longevity (Hall and Jones, 2007).

to consumption. The first-order condition to this problem yields

$$m^* = \frac{\frac{\eta_L(m^*)}{\eta_u(m^*)}}{1 + \frac{\eta_L(m^*)}{\eta_u(m^*)}} y.$$

Note that $\frac{m^*}{y}$ is monotonically increasing in $\frac{\eta_L(m^*)}{\eta_u(m^*)}$. If the longevity and utility functions are both of the constant elasticity form, a constant share of income is spent on health. Hence, medical expenditures do not grow faster than income as income rises.

Hall and Jones (2007) note that if utility is given by $u(c) = b + \frac{c^{1-\sigma}}{1-\sigma}$ where b is positive, then the elasticity of utility will not be constant. In fact, assuming a risk aversion parameter $\sigma > 1$ yields a declining elasticity of utility when consumption rises. For a constant elasticity specification of the longevity function, this implies a rising share of income is spent on health as income rises. Technology can also induce a rising share of income devoted to medical expenditures if the elasticity of the production function decreases more slowly than the elasticity of utility as spending rises.

Interactions between income and technological change can be studied by looking at the marginal utility of spending on health. At some value m , we have

$$v_m(m, z, y) = L_m(z, m)u(y - m) - L(z, m)u_c(y - m)$$

This marginal utility unambiguously decreases with m given assumptions on concavity. Furthermore, this marginal utility unambiguously increases in income at every m if $L_m(z, m) > 0$. On the other hand, increases in z yield an ambiguous effect on the marginal utility. We obtain:

$$v_{mz}(m, z, y) = L_{mz}(z, m)u(y - m) - L_z(z, m)u_c(y - m)$$

which is positive if the first term dominates the second. For example, suppose a change in z that has nothing to do with health care. Then, $L_{mz}(z, m) = 0$ and thus the improvement increases the opportunity cost of spending on health. Spending on health would be

reduced. Suppose however, technological change which expands treatment to a group where $L_m(z, m) = 0$ at some level of z . Then, $L_{mz}(z, m) > 0$, as now the new treatment allows for medical spending to be productive. However, the magnitude of that change in induced productivity must be larger than the induced change in the level of L through $L_z(z, m)$. In this case, spending increases. As discussed in the introduction, there are many reasons to believe that some of the improvements that were encountered suggest $L_{mz}(z, m) > 0$. However, this effect must be large enough to yield increased spending.

Turning to the relationship between income and technological change, we have that

$$v_{mzy}(m, z, y) = L_{mz}(z, m)u_c(y - m) - L_z(z, m)u_{cc}(y - m)$$

which has ambiguous sign. If positive, both are complements for the growth in spending. If negative, both are substitute. For them to be complements, the condition can be rewritten as

$$\frac{L_{mz}(z, m)}{L_z(z, m)} > \frac{u_{cc}(y - m)}{u_c(y - m)}$$

The right hand side is negative. Hence, a sufficient condition for both to be complements is that $L_{mz}(z, m) > 0$. It is easy to show that $v_{mz}(m, z, y) > 0$ implies $v_{myz}(m, z, y) > 0$. The magnitude of these derivatives is unknown and therefore is fertile ground for empirical investigation.

A simple calibration exercise shows that complementarity effects (such as the complementarity of income and technology in health care spending) can be important. According to the Human Mortality Database (HMD), period life expectancy at birth has risen from 70.4 to 77.7 years from 1965 to 2005. Using National Health Expenditure Accounts (NHEA) data, average personal health spending was \$570 in 1965 (in 2005 dollars, inflated using CPI) while it was \$5,738 in 2005. Take the same utility function as in Hall and Jones (2006), $u(c) = b + \frac{c^{1-\sigma}}{1-\sigma}$, and a simple functional semi-log specification for the production function, $L(z, m) = L_{min} + z \log(m)$. This provides a good approximation since life expectancy has increased linearly by roughly 2 years every 10 years and the rate of growth of health spend-

ing has been relatively constant. Although $L_{mz}(z, m) = 1/m > 0$ implies technology and income are complements, whether technology increases spending will depend on parameter values. We calibrate parameter values to match the rise in longevity and health spending over the period 1965-2005.⁴

With 1965 technology we can solve for optimal medical expenditures given income in 2005. This tells us by how much medical expenditures would have risen keeping technology constant. Medical expenditures would have increased by \$3,108, or about two thirds of the observed increase. The income elasticity of medical expenditures is therefore 1.69 using the 1965 technology. In a second counterfactual, we keep income constant at its 1965 level and bring the technology to its 2005 level. Optimal medical expenditures increase by a mere \$354: technology does not appear to play a role in increasing health spending. More importantly, the sum of those two independent effects is \$3,461, which falls short of the observed (and predicted) \$5,168 increase in medical expenditures over the period. We attribute the unexplained portion to a complementarity effect. Thus, an additional \$1,860 increase in health spending, representing 36% of the total, arises from technology and income improving concurrently. Optimal medical spending is more sensitive to income with a more productive technology.

This illustrative and simplified example shows that complementarity effects between technology and income may be important. But the static model may not be sufficiently realistic. For example medical expenditures are not constant over the life-cycle. They increase rapidly toward the end of life. The static model may also not be best suited to study other factors, such as the expansion of health insurance, which has changed the marginal cost of spending on health. The marginal cost also varies over the life-cycle (for example due to Medicare), as do mortality risks and income. There might also be other

⁴We use somewhat arbitrary numbers to calibrate L_{min} . We take the 1950 life expectancy, 68 years, as an estimate of L_{min} in 1965. We assume that 50% of the rise in longevity is due to factors other than health spending (Hall and Jones assume 40%) which yields L_{min} in 2005 of 71.7 years. Using these numbers we can solve for z in 1965 and 2005, which yields 0.38 in 1965 and 0.70 in 2005. The annual rate of growth in the technology parameter z is thus 1.5%. Using the two instances of the first-order condition above (1965 and 2005), income per capita in each period, we can solve for the preference parameters consistent with the observed growth in medical expenditures. Per capita income in 1965 is \$11,704 while it is \$42,482 in 2005 (all 2005 dollars) according to Penn World Tables. We obtain $b = 0.228$ and $\sigma = 1.424$.

benefits to investing in health, such as the ability to enjoy leisure (which may be difficult when one is sick). Income may depend on health through labor supply, which is not modeled in the stylized model. Finally, since the strength of complementarity effects will depend on both technology and preference parameters, we may want to estimate these parameters from micro-data. Hence, we construct - and subsequently estimate on micro-data - a more sophisticated model that includes many realistic features of the decision environment faced by agents. This more sophisticated model allows one to assess simultaneously the effect of each factor on health spending and longevity, and examine welfare effects.

3 Model

3.1 Environment

Consider a household head who starts his life-cycle at age $t = 25$. He has wealth, w_t , and health status, h_t , the latter taking three possible values corresponding to the self-reported health status scale we will use $\{1 = \text{poor or fair}, 2 = \text{good}, 3 = \text{very good or excellent}\}$. Initial wealth and health status are given by w_{25} and h_{25} . He has a main job, with health insurance, f_t , taking three possible values $\{1 = \text{no coverage}, 2 = \text{employer-tied coverage}, 3 = \text{retiree coverage}\}$ and earnings, y_t^e .

The agent chooses consumption, c_t , and medical expenditures, m_t , at each age. His earnings, y_t^e , are stochastic. Starting at age 50, the agent can choose to quit work ($p_t = 1$ if working, $p_t = 0$ if not). But this decision is not irreversible. He can elect to return to work. At age 62, he becomes eligible for Social Security benefits, y_t^{ss} , which he may claim or not, ss_t ($ss_t = 1$ if benefits are claimed, zero if not). At age 65, he becomes eligible for Medicare. After age 70, there is no work nor claiming decision (and everyone is retired).

Health follows a persistent stochastic process, which depends on age, current health, and medical expenditures. Medical expenditures are incurred voluntarily and improve health. This improvement process has two benefits. First, it increases the amount of time available for leisure and work (by reducing time being sick) and thereby increases the quality of life

in future periods. Second, it lengthens life. Longevity is endogenous in the model. But there is a practical limit on human life, set at age 110.⁵ If the agent has insurance, medical expenditures are partially paid for by an insurer, either non-governmental (employer-tied or retiree) or governmental (Medicaid or Medicare). Agents with employer-tied coverage lose coverage if they quit before the age of Medicare eligibility. We follow French and Jones (2011) who assume that the employer does not offer insurance if the agent returns to work at a later date. This is not the case for jobs with retiree insurance coverage. Those workers retain coverage even if they quit their job. Finally, if resources are sufficiently low, the agent qualifies for Medicaid.

3.2 Preferences

The agent derives utility from consumption and leisure. The amount of leisure time available depends on whether the agent works and on his health status. We specify the following utility function

$$u(c_t, h_t, p_t) = \alpha_h + \frac{(c_t^\gamma (L - \varsigma_p p_t - \phi_h)^{(1-\gamma)})^{(1-\sigma)}}{(1-\sigma)}$$

where L is the maximum annual amount of leisure available (set to 4000 hours), and $\varsigma_p = 2000$ is the number of hours worked when working full-time. The parameter α_h is the baseline utility level in health state h_t which governs the utility benefit of living longer. We set $\alpha_1 = 0$. Leisure time depends on health through a leisure penalty, ϕ_h , with $\phi_3 = 0$ imposed as a normalization (L thus represents the maximum amount of leisure available in very good / excellent health). The agent's discount factor is β , the coefficient of risk aversion is σ , and γ governs how consumption is valued relative to leisure. For ease of reference, collect the preference parameters to be estimated in the vector $\theta = (\alpha_2, \alpha_3, \gamma, \phi_1, \phi_2, \sigma, \beta)$.

⁵The maximum age is set at 110 for computational reasons. Solutions to the model are insensitive to this choice for higher maximum ages.

3.3 Resources

The agent has four potential sources of income. First, the agent has earnings if he works, y_t^e . Second, the agent has other income which includes spousal earnings as well as private pension income (annuities, etc), y_t^o . Third, the agent can collect social security benefits, y_t^{ss} , if eligible. Finally, he earns interest income on his non-pension wealth, rw_t , where r is the real rate of return and w_t is current wealth. Total net income is given by

$$y_t = \tau_n(y_t^e, y_t^o, y_t^{ss}, rw_t)$$

The net income function, τ_n , takes account of Federal taxes as well as Social Security and Medicare contributions (see Appendix A for details). The real rate of return is set at 4%.

Resources available for spending (on either consumption or medical expenditures) are given by

$$x_t = w_t + y_t$$

If those resources fall below a floor, x_{min} , government transfers are provided. The formula for transfers is given by

$$tr_t = \max(0, x_{min} - x_t)$$

Out-of-pocket medical expenditures are given by

$$oop_t = \psi(f_t, t, tr_t)m_t$$

where the co-insurance rate, ψ , depends on insurance coverage, age and transfer receipt. Prior to age 65, the agent who does not have insurance and receives transfers is assumed to be on Medicaid. He faces a lower co-insurance rate than without insurance.⁶

The resource constraint is completed with the equation for wealth accumulation. Agents

⁶We did not allow for a deductible & co-insurance rate structure. First, deductibles are heterogeneous and unknown to us in the data. Hence, it is not clear how we could use total and out-of-pocket medical expenditures to estimate deductibles. Second, we will rely on historical information on aggregate out-of-pocket and total medical expenditures to compute co-insurance rates. Hence, a two-part pricing schedule would be difficult to implement.

cannot end the period with negative private wealth. Hence, there is a borrowing constraint. Wealth at the end of the period is given by

$$w_{t+1} = x_t + tr_t - c_t - oop_t$$

The earnings process is quadratic in age and features an AR(1) error structure:

$$\log y_t^e = \pi_0 + \pi_1 t + \pi_2 t^2 + \eta_t$$

where the earnings shock is given by $\eta_t = \rho\eta_{t-1} + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.⁷

Other income, y_t^o , which includes spousal earnings and private pension income, is also quadratic in age and depends on the sum of earnings and Social Security income of the agent head. This is done to preserve the correlation between own and other income at the household level. Because cohort effects will be present in the data and institutions differ across cohorts, the model will be constructed for an agent born in 1940. That agent was 25 in 1965. We do not model changes in the tax, insurance and Social Security systems over time. Instead, we assume the 1990 environment prevails. In the model, this corresponds to the agent being age 50, when he starts making labor supply decisions. The Social Security system he faces was shaped almost entirely by the 1983 Social Security reform.⁸

The earnings base for computing Social Security income is the average indexed monthly earnings (AME), ame_t , which takes the average of the highest 35 years of earnings. Details on the modeling of Social Security and the application process is found in Appendix A.

⁷In principle, earnings could depend on health status. However that effect likely occurs through hours worked rather than wages (Currie and Madrian, 1997). Since workers choose labor supply beyond age 50, (lifetime and current) earnings will effectively depend on health.

⁸An alternative would be to build on changes over time in tax and pension rules. Assuming these were anticipated by our agents would not create a drastically different world than what is assumed here since the important decisions agents make occur after age 50 and thus agents would anticipate the same Social Security and tax system we use. Of course, changes to taxes are likely unanticipated but this is harder to build into the model as it would require to model expectations. Our approach of a fixed tax and Social Security system is similar to that followed by a number of authors (e.g., French, 2005 or DeNardi, French and Jones, 2010).

3.4 Health Process

Health follows a dynamic process that depends on current health, $h_t = k$ ($k = 1, 2, 3$), age, t , and medical expenditures, m_t . We specify the following dynamic multinomial model for health transitions

$$\Pr(h_{t+1} = j | h_t = k, t, m_t) = \frac{e^{\delta_{0jk} + \delta_{1j}t + \delta_{2j} \log m_t + \delta_{3j} \log m_t^2}}{\sum_{j'} e^{\delta_{0j'k} + \delta_{1j'}t + \delta_{2j'} \log m_t + \delta_{3j'} \log m_t^2}}$$

where $j = 1$ is the base category (fair or poor health). The productivity of medical expenditures will thus depend on the parameters $\{\delta_{2,j}, \delta_{3,j}\}_{j=2,3}$. Health is persistent, which is captured by the parameters, $\delta_{0,jk}$, and it depreciates with age, $\delta_{1,j}$. This health production function is consistent with the view that health is a stock which depreciates over time and can be replenished by investments (Grossman, 1972). The dependence on medical expenditures is flexible and in particular allows for a concave relationship between health and medical expenditures.

The likelihood of death depends on age and health and follows a Gompertz hazard function such that

$$P_{d_{h,t}} = \Pr(d_{t+1} = 1 | h_{t+1} = k, t) = 1 - e^{-e^{\delta_6 t} e^{\delta_7 k}}.$$

Thus mortality depends indirectly on medical expenditures through their effect on health status.

3.5 Maximization Problem

Denote the state space at age t as $s_t = (h_t, \eta_t, ss_t, f_t, ame_t, w_t)$. The agent's maximization problem can be written as a Bellman equation

$$V_t(s_t) = \max_{c_t, m_t, p_t, ss_{t+1}} u(c_t, h_t, p_t) + \beta \sum_h (1 - p_{d_{h,t}}) p_{h,t} E_{\eta_{t+1}} V_{t+1}(s_{t+1})$$

where $p_{d_{h,t}}$ is the mortality probability given health and age, and $p_{h,t}$ is the probability of transitioning to state h_t given age, current health and medical expenditures. The term $E_{\eta_{t+1}}$ is the expectation operator with respect to the distribution of earnings shocks given current earnings. This optimization problem is subject to the law of motion for w_t , ame_t , constraints on the transitions of other state variables, and constraints on the choice set. We solve for optimal decision rules by backward recursion. Details on the solution method are given in Appendix E.

4 Data and Estimation

We focus on males as their labor supply behavior is more likely to be consistent with the model (i.e., working full-time prior to age 50 with no interruptions). We use two main longitudinal datasets to estimate auxiliary processes and parameters of the model. First, we use the Panel Study of Income Dynamics (PSID) for data on income, wealth and work. We use the 1984 to 1997 waves as well as the wealth surveys of 1984 to 2005 (7 waves). Details on sample selection and the construction of the variables used in the PSID are given in Appendix B.

The PSID has data on health but not on total medical expenditures of the agent. Furthermore, mortality follow-up in the public version of the data is incomplete and leads to low mortality rates (French, 2005). Instead, we use the Medical Expenditure Panel Survey (MEPS) to estimate the health process. Members of the panel are initially drawn from National Health Interview Survey (NHIS) respondents and remain in the panel for two years. Self-reported health is measured on a 5-point scale (poor, fair, good, very good, excellent); we group these in 3 categories to save on the dimension of the state-space {poor or fair, good, very good or excellent}. The MEPS dataset is also used to estimate the co-insurance function, $\psi()$. Data on medical expenditures is detailed. It does not include nursing home expenditures. Since nursing home expenditures are conceptually closer to consumption than to investment in health, this omission is probably consistent with the model. Details on

sample selection and the construction of variables used in MEPS are given in Appendix B.⁹

Following recent papers estimating life-cycle models similar to the one presented here (e.g. French, 2005), we use a two-step estimation strategy to estimate the parameters of the model. We first estimate auxiliary processes (earnings, health, etc.) and then estimate preferences using the method of simulated moments.

4.1 Auxiliary Processes

4.1.1 Resources

The earnings and “other income” processes are estimated using PSID data. Parameters of the earnings process are estimated by fixed effects regression. The AR(1) term is estimated from the residuals of the process using minimum distance techniques. Earnings are hump-shaped and peak around age 49 years. The estimate of the autocorrelation coefficient ρ is 0.978 and the variance of the innovation is $\sigma_\varepsilon^2 = 0.008$ (see Appendix C for details on the estimation). The “other income” process is estimated by instrumental variables using education as an instrument (French, 2005). “Other income” is also hump-shaped, with a peak at age 51. The coefficient of earnings and Social Security benefits of the agent head π_4 is 0.306. We report more details in Appendix C.

4.1.2 Health and Mortality

We need to address the potential endogeneity of medical expenditures when estimating the health process. Indeed, medical expenditures may depend on the incidence of a health shock between waves. On the other hand, unobserved heterogeneity is unlikely to be a large source of bias as the health process controls for current health. Nevertheless, we add controls for risk factors when estimating the production function (smoking and obesity).¹⁰ In this

⁹Both PSID and MEPS (public version), despite having information on insurance, lack information on retiree health insurance coverage. The model assumes this coverage is constant prior to retirement. We use the Health and Retirement Study (HRS) to compute retiree health insurance coverage rates for those born between 1935 and 1945 when they were age 50 to 55.

¹⁰We have also estimated the production function with a large vector of health and socio-demographic measures. Results were largely insensitive to these additional controls. Hence, we retained the simpler specification with controls for current self-reported health, smoking and obesity.

context, a valid instrument is one that 1) predicts medical spending 2) but is uncorrelated with the incidence of a health shock given current health and risk factors. Lagged income is a potential candidate. Due to the persistence of income, it predicts future income and thus future medical spending as found in studies looking at the effect of income on spending. However, it is unlikely to be correlated with the incidence of a health shock given current health and risk factors. Current income is not a valid instrument due to the potential for health shocks to affect current earnings. As detailed in Appendix D, we use a control function approach (Peltrin and Train, 2010). We first estimate an equation for the log of medical expenditures given current health, risk factors and the log of current income. The estimated income elasticity is 0.124 and is highly statistically significant (partial $F=26.7$). A measure of the unobservables that may be correlated with future health is the residual from that regression, which we then plug into the health process. We estimate the multinomial logit by maximum likelihood. We account for first-step estimation noise by bootstrapping the entire procedure to compute standard errors. The estimated effects reveal moderate positive effects of medical expenditures on health and the relationship is concave. A 50% increase in medical expenditures increases the probability of being in excellent health in the next period by 6.5 percentage points at \$5,000 of spending (22% are in excellent health in the estimation sample). Estimation results are reported in Appendix D.

Not surprisingly, the maximum likelihood estimates of the mortality process reveal that better health is associated with lower mortality risk. Combining the mortality and health process estimates, we estimate the marginal effect of medical expenditures on mortality risk. Figure 1 shows the resulting mortality rates by medical spending level and current health status for individuals age 65+. Mortality falls with increased spending, but the effect diminishes as the level of spending increases. The first dollars of medical expenditures are more productive in almost all states, in particular in good health.

4.1.3 Other Institutional Parameters

The resource floor is set at \$10,000. The real rate of return is set at 0.04. We construct co-insurance rates, $\psi()$, using MEPS data. We take the ratio of out-of-pocket medical expenditures to total medical expenditures as our estimate of the co-insurance rate (see French and Jones, 2011, for a similar methodology). This yields a median co-insurance rate of 25% for individuals with tied-employer insurance, 7% for those receiving government transfers (i.e. those on Medicaid), 100% for those without insurance and ineligible for Medicaid and 20% for those on Medicare. Appendix A provides details on the construction of these shares and the rationale behind other numbers.

4.2 Preference Parameters

The remaining parameters to estimate are $\theta = (\alpha_2, \alpha_3, \gamma, \phi_1, \phi_2, \sigma, \beta)$. We estimate these parameters by the method of simulated moments (MSM) (Gourinchas and Parker, 2002; French, 2005). This is done by matching moments from the data with moments obtained from simulations of the model. The moments chosen are: average wealth over 5-year intervals between ages 35 and 70; average medical expenditures over 5-year intervals between ages 35 and 85; proportion of individuals working, by health status, at 2-year intervals between ages 56 and 68; and finally, mortality rates over 5-year intervals between ages 50 and 95. These profiles are constructed using the methodology outlined in French (2005) and accounting for cohort and family composition effects. Appendix E gives details on the construction of each profile.

The wealth profile primarily provides information on σ and β following the usual identification arguments. The labor force participation moments by health status provide information on γ , ϕ_1 and ϕ_2 , keeping σ and β constant. Assuming (σ, β) are determined by previous information, the medical expenditures profile helps determining (α_2, α_3) given that the health process is estimated in the first step.

We have 50 moments for 7 parameters. The overidentification test statistic therefore has a χ^2_{50-7} distribution. More details on the properties of the estimator are found in Appendix

4.2.1 Estimation Results

Table 1 reports parameter estimates along with standard errors. We obtain an estimate for the general curvature of the utility function, $\hat{\sigma} = 3.365$ ($se = 0.958$). Given our estimate of the consumption share in the utility function, $\hat{\gamma} = 0.436$ ($se = 0.005$), we obtain the coefficient of risk aversion, keeping labor supply fixed, as $-(\hat{\gamma}(1 - \hat{\sigma}) - 1) = 2.03$ (French, 2005). Hence, our estimate of the coefficient of relative risk aversion is close to estimates reported in the literature, and very close to the estimate of 2 used by Hall and Jones (2007). We estimate that agents are patient, with a discount factor estimate of $\hat{\beta} = 0.984$ ($se = 0.036$). This estimate is slightly lower than the parameter estimate of 0.992 used in Hall and Jones (2007). These parameters are statistically significant at the 1% level. The estimates of the amount of leisure time lost when in poorer health are $\hat{\phi}_2 = 371.6$ ($se = 442.3$) and $\hat{\phi}_1 = 696.1$ ($se = 708.3$), representing 9.2% and 17.4% of maximum leisure time available. However, these parameter estimates are imprecise and we cannot reject a value of zero. Part of the reason for the imprecision may have to do with the fact that we only model labor force participation and not hours worked. Finally, estimates of α_1 and α_2 are respectively 0.190 ($se = 0.149$) and 0.229 ($se = 0.047$), with only the latter being statistically different from zero. Overall, utility increases with health, which has an impact on the desire of agents to invest in health.

4.2.2 Model Fit

The model fits the data well given that we only have 7 preference parameters and none of these parameters depend on age. The overidentifying restriction test statistic takes a value

¹¹Since the baseline utility levels are quite sensitive to the choice of other parameters, we rescale as

$$\alpha_h^* = -\alpha_h \frac{(x_{min}^\gamma L^{1-\gamma})^{(1-\sigma)}}{(1-\sigma)}, h = 2, 3$$

Hence, the estimates of α_2 and α_3 should be interpreted in units of baseline utility measured at x_{min} and maximum leisure.

of 164.8. Formally, the restrictions are rejected (p -value < 0.01). However, inspection of the simulated profiles in Figure 2 shows a relatively close fit. The simulated moments are for the most part within the confidence intervals of the moments estimated from the data. There are three exceptions. First, we predict a decline in wealth after age 65 which we could not detect in the data. One possible explanation is that we did not incorporate bequests in the model (French, 2005). The second exception is labor force participation of individuals in poor health at ages 56 and 58. We over-predict labor force participation at those ages for this group. Two explanations appear plausible. The first is that we did not model disability insurance, which provides another exit route to retirement for individuals in poor health. The other is that we did not model private defined-benefit pensions, which may provide an incentive to stop work early. Despite the fact that we did not allow any of the preference parameters to depend on age, the model is able to capture the overall patterns of declining labor force participation without any direct dependence of utility on age. The third exception is that we over-predict mortality at advanced ages while under-predicting it at younger ages. However, as we show below the life expectancy estimates implied by the model are roughly consistent with what we observe from mortality data (78.1 years old compared to 77.7). These minor deviations are unlikely to lead to very different simulation results for the scenarios we investigate below.

4.2.3 Income and Insurance Elasticities

Since the response of medical spending to income and co-insurance rate variation is central to the questions we asked, it is worth investigating the elasticities that the model generates. To do this, we use simulated data generated by the model. We focus on individuals younger than 50 since their labor supply is fixed and, thus, income and co-insurance variation is exogenous, conditional on initial conditions. We regress log spending on health on the log of the co-insurance rate. The coefficient on log income can be interpreted as an elasticity. We control for age by including five-year age dummies. In some specifications, we control for current health and assets. Finally, we also estimate a fixed effects regression. Estimates

of the income and co-payment elasticities obtained by regression are reported in Table 2.

The income elasticities range from 0.513 to 0.592. These elasticities fall between macro (closer to 1) and micro (0.2-0.4) estimates of the income elasticity of health spending. Estimates are closer to those obtained by Acemoglu et al. (2013). They report a central estimate of 0.7. Hall and Jones (2007) obtain much higher elasticities (higher than 2) as they are able to explain the rise in the fraction of income devoted to health only as a result of income growth.

As for the co-pay elasticity, we obtain regression estimates of -0.555 without controls and -0.570 with controls. This is larger in magnitude than estimates from the RAND Health Insurance Experiment, which are closer to -0.2 (Manning et al., 1987). There are a number of reasons why we obtain larger elasticities. First, the RAND Health Insurance Experiment varied co-insurance rates exogeneously in an environment where out-of-pocket expenditures were subject to a limit (Manning et al., 1987). Such a stop loss on health spending naturally results in lower elasticities. Second, our “random” assignment of insurance status is permanent until age 65 (or until retirement). The assignment of co-insurance rates was limited to a few years in the RAND Health Insurance Experiment. This could explain why our elasticity estimate is larger.

We can also investigate how health spending varies by insurance status near age 65. In Figure 3, we report average simulated total medical expenditures by age and insurance status. We see that for those with retiree coverage, medical expenditures hardly jump at age 65. There is a small increase in spending for those with employer-tied coverage, from \$7,253.8 to \$8,028.8. This is due to the fact that a fraction of those with employer-tied coverage quit work and hence lose health insurance coverage. The greatest change in medical expenditures at age 65 is found for the uninsured, who spend \$3,548.9 on average at age 64 compared to \$8,529.6 at age 65. This jump represents an increase of 140% in health spending or a co-pay elasticity (using the effective change in co-pay) of 1.83. Interestingly, there is evidence of intertemporal substitution as medical spending at age 65 is actually higher for the previously uninsured than for those with continued coverage (\$8,529.6 vs. \$7,488.6). This is consistent

with evidence from Card et al. (2008) who find that health care use appears to increase discontinuously at age 65 for those more likely to lack health insurance coverage prior to age 65.

5 Counterfactual Simulations

With the estimates of preferences and technology obtained in section 4, we simulate the experience of a particular cohort under various counterfactual scenarios. We ask the question: how would the 1940 cohort, which was 25 years old in 1965, have fared had changes affecting financial resources, insurance coverage, technology and risk factors not taken place? To answer this question, we look back at some of the important factors that may have changed over the period up to 2005 and that may have affected both health spending and longevity. We roll those factors back to 1965 levels, which we call the 1965 environment. We then successively introduce those changes and evaluate their effect.

5.1 The 1965 compared to the 2005 environment

Changes between 1965 and 2005 can broadly be grouped into four areas of change: financial resources, the generosity of health insurance, technology, and “other” factors.

Financial resources: The income available for consumption and health spending has increased over the years. As in Hall and Jones (2007) we use growth in real per capita GNP, which averaged 2% annually over this period. Affecting after-tax income, taxes were higher in 1965. Gouveia and Strauss (2000) compute average tax rates by income from 1966 to 1989. We use the 1966 tax function instead of the 1989 tax function in our 1965 environment. Finally, the generosity of Social Security benefits has increased over time, primarily due to two effects. First, generosity has increased due to changes in the computation of the primary insurance amount (PIA), which went from replacing 30% to 40% of the *ame*. Second, the 1983 Social Security reform expanded the delayed retirement credit to 7% for those born in 1940. We eliminate this credit in the 1965 environment.

The generosity of health insurance: After the introduction of Medicare, three key changes have increased the generosity of health insurance in the United States. First, there has been a decline in the uninsured among the non-Medicare population, from 26% in 1962 to 20% in 2005. Second, there has been an expansion of the generosity of employer provided health insurance. We calculate that co-payments decreased from an average of 60% in 1965 to 20% in 2005. Third, changes in Medicare coverage have increased the generosity of benefits. A few years after Medicare’s 1965 introduction, out-of-pocket expenditures were equal to 30% of the program’s total spending. In 2005, they represented 20% of total outlays according to our calculations.

There are two other sets of factors that may have affected both health and spending: technology and “other factors”. Both are hard to measure from outside sources. Hence, we review the relevant evidence and resort to a calibration exercise.

Technology: Cutler and McClellan (2001) give various examples of important changes in productivity that may have improved survival with overall positive benefits. They point to a 1.5% annual decline in the quality-adjusted price of treating heart attacks as a measure of technological progress. Similarly, Skinner and Staiger (2009) show that in treating heart attacks there is roughly a 3 percentage point difference in survival between hospitals with rapid diffusion of new treatments and those with low diffusion. Improvements in risk adjusted survival average 0.5% year over the period 1985-2004. ¹²

Other factors: At the same time, other factors have likely affected the health of this cohort. The first obvious candidate is smoking, which has large impacts on mortality. The relevant measure for understanding its effect on life expectancy is the lifetime exposure of a given cohort rather than point-in-time prevalence of smoking (Preston, Gleib and Wilmoth, 2011). The former increased until the mid 1980s while the latter declined over the period.

¹²Medical prices, as measured by the medical CPI, have increased at a rate close to 2% per year. However, as discussed in Berndt et al. (2001), this increase in prices likely reflects changes in type and quality of procedures. In this paper, we make the assumption that medical prices, relative to consumption goods, remain constant between 1965 and 2005.

Estimates of mortality that can be attributed to smoking range from 10% in 1965 to 24% at peak lifetime exposure in 1985. Preston, Gleil and Wilmoth (2011) estimate that life expectancy among men at age 50 would have been 0.9 years higher in 2002 if the increase in lifetime smoking had not taken place. Another key factor is the increased prevalence of obesity, starting in the mid 1970s. Ruhm (2007) uses NHANES data from 1961-62 to 2004 to estimate comparable obesity rates for males and females, using measured rather than self-reported weight and height. For males, obesity rose from 13.4% to 31.5%, or roughly 2.1% per year. Both these factors tend to support the view that factors other than financial resources, health insurance and technology may have had an effect on survival rates over the period 1965-2005 - in this case, a negative one. On the positive side, improvements in air pollution may have lead to an independent reduction in mortality rates. One study argues that as much as 15% of the increase in life expectancy in 51 major U.S. cities during the 80s and 90s may be attributed to improvements in air quality (Pope et al., 2009). Hence, it is unclear whether these “other factors” in aggregate had a net positive or negative effect on mortality rates over the period.

We model technology and “other” factors in terms of changes in two parameters of the model. Technological change is modeled as a change in the productivity parameters of the production function $\delta_{2,j}$ (see section 3.4). Let κ_1 be the rate of growth in productivity. Thus, $\delta_{2,j}^{1965} = e^{-\kappa_1 40} \delta_{2,j}$. We define the annual rate of growth of mortality due to “other factors” as κ_2 . Hence, we rewrite, $P_{d,h,t}^{1965} = e^{-\kappa_2 40} P_{d,h,t}$. There are no micro-data sources that would allow us to directly estimate κ_2 and κ_1 . If panel data of the type used in MEPS existed in 1965, we could estimate directly the 1965 production function. Cross-sectional data featuring health and total spending measures is available during that period. However, it does not include the self-reported health measure we use in MEPS. Hence, we resort to a calibration exercise using the model and aggregate data in 1965. We have two unknown parameters (κ_1, κ_2). We consider an environment with financial resources and insurance as they were in 1965. Let the simulated average medical expenditures from the model in that scenario with values κ_1 and

κ_2 be defined as $\tilde{m}_{1965}(\kappa_1, \kappa_2)$. Similarly, simulated life expectancy is given by $\tilde{e}_{1965}(\kappa_1, \kappa_2)$. The actual 1965 values are obtained from National Health Expenditure Accounts and period life-tables for 1965, $m_{1965} = 569.8$ and $e_{1965} = 70.01$. We solve for the values of κ_1 and κ_2 such that we match these values. These are separately identified. Relative to 2005, an increase in κ_1 tends to lower both health spending and longevity in 1965 while an increase in κ_2 increases longevity while decreasing health spending. The values which solve this system of two equations are $\hat{\kappa}_1 = 0.013$ and $\hat{\kappa}_2 = -0.009$. Hence, these estimates suggest that negative factors such as the increase in lifetime prevalence of smoking in the first part of the period and the prevalence of obesity outweighed positive factors such as improvements in air quality, and that productivity in health care improved at a pace of 1.3% per year. These estimates are consistent with other estimates of technological change in health care during the period.

5.2 Contributions to Historical Growth in Spending and Longevity

We now perform the following counterfactual experiment. Imagine that starting from 1965, we introduce each of the changes separately and look at health spending and longevity. We can then compute the contribution of each factor to the growth of health spending and longevity observed over the period. As we show in section 2, there is potential for complementarity effects. Hence, under the assumption that the model captures the most important factors to growth in spending and longevity, the residual growth unexplained by the sum of each contributing factor reflects such effects.

In Table 3, we report the results of the simulations in terms of total medical expenditures, out-of-pocket medical expenditures and life expectancy. We also report as the last outcome a welfare measure based on the comparison of average expected utility at age 25 in each scenario. For scenarios where expected utility is larger than in the 1965 environment, we estimate the fraction of annual consumption in the 2005 environment which would have to be taken away for this average individual to be as well off as in the 1965 environment. Hence, it is a measure of compensating variation (CV).

When letting income grow at 2% per year from the 1965 baseline and implementing tax and Social Security changes, health expenditures increase to \$771.7 from \$569.1 at the baseline, a 34% increase. The income elasticity is thus 0.29 in the 1965 environment. This suggests that the income elasticity has increased over time since our estimate in the 2005 environment was closer to 0.55 (Table 2). Life expectancy only increases by half a year due to income growth alone. Most of the gain occurs prior to age 50 as remaining life expectancy at age 50 barely changes. Because the share of income devoted to health care does not rise (it decreases), consumption expenditures increase. This leads to a substantial welfare gain, representing 26.7% of average consumption expenditures in the 2005 environment.

Improvements in insurance from the 1965 baseline do not increase medical expenditures by a much larger amount. With 2005 insurance parameters, average medical expenditures increase to \$929.2, a 63% increase. Longevity increases by 0.3 years due to the expansion of insurance, most of it again prior to age 50. The welfare gains from the expansion of insurance are modest. They represent 3.3% of annual consumption expenditures in the 2005 environment.

Hence, both the growth of insurance and income independently cannot explain the rise in health spending and longevity. Technological change has much larger effects. Allowing for productivity growth in the 1965 environment increases health spending from \$569 to \$1,972, a 247% increase. The increase in longevity is large, at 9.6 years and most of it is due to improvements at older ages (7.9 years out of 9.6). Welfare gains, as a result of technology represent close to two thirds of annual consumption in the 2005 environment. We can compare this result to the value of life. Aldy and Viscusi (2004) suggest that \$200k is a reasonable estimate for the value of a life year. This suggests that the additional 9.6 years are worth roughly \$1.9m. Lifetime consumption (without discounting) is \$2.8m in the 2005 environment. Thus \$1.9m represent roughly two thirds of life-time utility. Hence, technological change accounts for a large share of the overall welfare gains over the period 1965 to 2005 and our estimates are consistent with a value of a life year close to \$200k.

The negative mortality effect of other factors on longevity in 1965 is large (5 years).

However, the more important comparison is the one between the technology scenario and the 2005 scenario which imposes the trend in these other factors. Longevity is 1.3 years lower in the “other factors” scenario, compared to the technology scenario. This is close to the estimate of Preston, Gleib and Wilmoth (2011) who report that male life expectancy would be 0.9 years higher without the trend in smoking.

In Table 4, we compute the contribution of each factor to the change in medical spending and life expectancy over the period 1965-2005. Income and insurance together account for less than 12% of the overall increase in medical expenditures. Technology accounts for 30%, while the deterioration of health - probably due to smoking and obesity - accounts for less than 1%. This leaves 57.3% for complementarity effects since by construction allowing for all factors yields the 2005 spending level. In other words, the estimates suggest that the observed growth in health care spending would not have occurred if these factors had not changed together. A similar story emerges with life expectancy, where most of the observed increase appears to be due to technological change. Other health trends (obesity and smoking) have considerably slowed down the growth of longevity. Interaction effects account for one third of the observed increase in life expectancy.

Overall, the welfare gains from higher health care spending appear substantial. The estimates suggest that the benefits in terms of better health and longevity far outweigh the costs in terms of higher health spending.

5.3 Contributions to the Expansion of the Income-Mortality Gradient

Over the last decades, many have documented that improvements in mortality appear to be mostly concentrated among those in the top of the income distribution (e.g. Schalick et al., 2000; Waldron, 2007) or among more educated households (Cutler et al., 2011). As a result, the socio-economic gradient has widened. One possibility is that as technological progress in health care took place, the rich spent disproportionately more than the poor on health. Another possibility is that the complementarity present in the model between income and technology also drives the evolution of the income-mortality gradient. In Figure 4, we

show that the model's predictions are consistent with this hypothesis. We plot simulated mortality rates by age for those who initially (at age 25) had income in the first tercile and in the third tercile. This is done both in the 1965 and 2005 environment. We can observe that the model predicts that differences in mortality rates by income were small in 1965 and that increased considerably by 2005. Both groups witnessed improvements in mortality but those gains are predicted by the model to have occurred disproportionately among those with higher incomes. In terms of life expectancy, those in the lowest tercile could expect to live another 21.4 years at age 50 in the first tercile of income compared to 21.3 in the 3rd tercile, i.e. essentially no difference between the terciles. In 2005, those in the lowest tercile could expect to live an additional 25.9 years compared to 28.6 in the highest tercile. Hence, the model predicts an expansion of the gradient by 2.7 years at age 50. This is consistent with studies linking lifetime income measures and mortality. For example, Duggan et al. (2008) use Social Security administrative records and find that differences in the age of death are of the order of 2-3 years between low and high levels of lifetime income. Using HRS data, De Nardi, French and Jones (2010) find a difference in life expectancy at age 70 of 3.6 years between those in the bottom quintile and top quintile of the income distribution.

5.4 Insurance Coverage and Intertemporal Substitution Effects

In recent years, proposals to reform health insurance in the U.S. have focused on expanding coverage prior to age 65 and on reforming Medicare to make it sustainable in the future. Expansion of coverage may increase health care spending, health and perhaps even reduce Medicare spending, if uninsured workers currently delay treatment until after they become eligible for Medicare. Our model is well-suited to study such effects as it allows for a response to changes in the price of investing in health along various margins: health care spending, retirement and saving. To gauge the potential for intertemporal substitution, we construct a scenario where we give uninsured workers access to the same insurance plan that workers have. This effectively also provides retiree health coverage to those with tied coverage in the model. We then simulate average health care spending and health status prior to and

after Medicare eligibility in that scenario, and compare them to the baseline.

The results, in Table 5, show that medical spending prior to age 65 increases for those without insurance coverage in the baseline (Uninsured). But there is no significant decrease in health spending post age 65 for this group. There is some evidence of intertemporal substitution for those with employer-tied coverage (Tied), but the effects are small. As expected, the fraction working decreases substantially prior to Medicare eligibility for those with tied coverage who do not have a reason to delay retirement anymore (Madrian, 1994). Between ages 60 to 64 the fraction that works decreases from 91% to 86% among those with tied coverage in the baseline. There is evidence of improved health for the uninsured, as the fraction in “very good or excellent health” increases from 80.4% to 87.9% between the ages of 60 and 64. Furthermore, their labor supply increases slightly. However, little of that health gain remains beyond age 65 and health spending is only slightly lower after age 65 for this group. Hence, this simulation suggests that it is unlikely that health spending at older ages will fall as a result of the provision of insurance coverage to the uninsured prior to age 65. The changes occur at ages prior to age 65 but little change is observed afterwards.

6 Conclusion

In this paper, we present a life-cycle model of health care spending, savings and retirement in an environment with uncertainty regarding health, earnings and mortality. The model is built on the idea that health is a stock that agents invest in because it provides utility benefits (e.g. it increases the amount of leisure available each year) and because it prolongs life. The model parameters are estimated on data for a representative cohort that lives through a period of rapid growth in health care spending. Estimates of preference parameters such as risk aversion and time preference are consistent with existing evidence from savings and retirement models. Other parameter estimates yield very sensible estimates of price and income elasticities of health spending and value of a life year estimates consistent with evidence from the literature. The estimated model enables counterfactual exercises to

reconstruct the changes experienced over the period 1965 to 2005 and to analyze the effect of potential reforms.

We first considered a set of scenarios aimed at computing the contribution of various factors to growth in health care spending and longevity. We implemented a calibration procedure to estimate the changes in technology and other factors affecting mortality which could rationalize the observed growth. We found, in the parameterization of the health-production function, that improvements in productivity of 1.3% per year, along with an independent adverse effect on mortality rates from smoking and obesity at a rate of 0.9% per year, could rationalize the growth observed in income and health insurance generosity over the period.

Starting from 1965, we estimated that each factor independently could not explain the observed growth in health care spending. But, when introduced simultaneously, their mutual reinforcement led to rapid growth in health care spending. Put simply, growth in income and insurance is not worth much without access to a productive health-production technology. According to our estimates, complementarity effects accounted for more than half of the increase observed in medical expenditures over the period. On the longevity side, the estimates suggest that technological progress is the main driver of growth over the period. Together they have produced important welfare benefits that may be worth as much as 76% of 2005 consumption expenditures. As for health care spending, complementarity effects are also important for explaining the growth in longevity, with an estimated one third coming from that source. We find complementarity has also implications for the evolution of health and mortality by income. The predictions from the model show a widening of the income-mortality gradient as a result of income growth and technological improvements. This arises even though in the exercise we keep income inequality constant. An interesting research question would be to investigate how widening income inequality, perhaps due to changes in the returns to schooling over the period may have played a role in explaining increasing inequality in health and mortality.

The presence of complementarity effects is potentially important for understanding how

relatively small differences in income and insurance growth across countries may lead to large aggregate differences in health-spending growth when technological progress is growing at the same pace across countries. Complementarity may strengthen these differences. The U.S. has had both a larger income growth and expansion of health insurance coverage than other developed countries after the Second World War. Even if technological progress has occurred at the same pace across countries, complementarity effects may explain why U.S. health spending growth has outpaced that of other countries, despite health spending being relatively inelastic to income and insurance. If one does not account for complementarities it is difficult to reconcile the observed growth with low income and co-pay elasticities. Furthermore, there is much insight to be gained from analyzing within a structural framework whether the growth in medical spending observed over the recent period was “worth it”. Our estimates suggest that the rise of health care spending increased welfare a great deal, with the largest contribution coming from technological progress.

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”For Online Publication” Appendix A Institutional Details

Taxes

Taxes are the sum of federal taxes, $\tau_f(y)$, the employee portion of the Social Security earnings tax and the Medicare tax. Federal tax is modeled using the following formula from Gouveia and Strauss (2000):

$$\tau_f(y) = a_0[y - (y^{-a_1} + a_2)^{-1/a_1}],$$

where y is the sum of all income sources. We use the 1989 parameters, $a_0 = 0.258$, $a_1 = 0.768$ and $a_2 = 0.031$. The Social Security earnings tax is 6.2% up to a maximum of \$97,500 in earnings. The Medicare tax is 1.5% of earnings and there is no maximum.

Social Security

The formula for updating the average indexed monthly earnings (AME) prior to age 60 is given by

$$ame_{t+1} = ame_t + \min(y_t^e, ssmax)/(35 \times 12)$$

where $ssmax = 97,500$. After age 60, the formula is given by

$$ame_{t+1} = ame_t + (\min(y_t^e, ssmax) - \chi_t ame_t)/(35 \times 12)$$

where χ_t is the probability that the AME will not be updated (French, 2005). This probability is computed by simulating earnings histories from the earnings process in the model and counting occurrence of updating using the true ame formula (i.e. the highest 35 years of earnings). This probability is 9.1% at age 60, and it reaches 59% by age 69.

The primary benefit is a piece-wise linear function of ame_t . The bendpoints for someone born in 1940 are \$477 and \$2,875: each dollar counts for 0.9 below the first bendpoint, for 0.32 in the second segment, and for 0.15 above the second bendpoint.

The full retirement age (FRA) for someone born in 1940 is 65 and 6 months which we

round to 65. If the agent claims prior to the FRA, he is penalized with a 6.7% reduction per year. Someone claiming at age 62 will receive 82% of his primary insurance amount (PIA). But if the agent claims after the FRA, he is granted a delayed retirement credit which for someone born in 1940 is 7% per additional year, compounded. Hence, someone claiming at age 70 will receive see his benefits increase by 40%. We denote this age adjustment $\zeta(t)$. The actuarially fair rate will vary across agents depending on their survival prospects.

At the time of claiming benefits, we adjust the ame_{t+1} such that

$$ame_{t+1} = PIA^{-1}(\zeta(t)PIA(ame_t))$$

This will permanently set ame_{t+1} to a value such that $PIA(ame_{t+1}) = \zeta(t)PIA(ame_t)$. Hence, we do not need to keep track of the age when someone claimed, t , in the state space.

The agent is allowed to work while collecting benefits. But he will suffer a benefit reduction if his earnings are above a limit, which we set at \$10,000 for this cohort. The penalty will depend on age. Prior to the FRA, the penalty is 50%. Hence, each dollar above the earnings limit cuts back current benefits by 50 cents. After the FRA, the penalty is 33%.

Government Transfers

The resource floor is set at \$10,000. This figure is derived from the Office of the Assistant Secretary for Planning and Evaluation (ASPE, 2008), which states that the maximum monthly benefit payable to a couple with one child under the Temporary Assistance for Needy Families (TANF) program was \$495 in 2006. That year, the average monthly benefit of recipients on food stamps (for a 3-person agent) was \$283. Hence, prior to age 65, the sum of TANF and food stamp benefits totaled \$778/month for a 3-person agent, or \$9,336/year (ignoring the lifetime TANF receipt limit). The Social Security Administration reports that the 2004 maximum monthly federal payment for SSI was \$552 for a single and \$829 for couples; including food stamps yields an annual total of \$7,620 for singles and \$12,180 for

couples.

If resources are below the resource floor, the agent is eligible for Medicaid if he does not have coverage through an employer or Medicare. As we detail below, we allow the co-insurance rate to be lower for such agents. When simulating agents using the income profiles described above, there are three periods over the life-cycle when agents are likely to receive transfers. First, this may happen at the beginning of the life-cycle when agents have saved little and may suffer from a large earnings shock. Fewer than 2% of agents with a head aged 35 years old or less receive transfers. The second period is between the ages of 50 and 62. There, some agents will leave the labor force and live on other income. This occurs mostly for agents with poor health and few resources. Between these ages, an average of 7% of agents receive transfers in the baseline simulations. The last age span where agents receive transfers is at the end of life. After age 85, some agents who receive little in the form of Social Security benefits see their other income decline (due for example to the death of a spouse). They spend down their wealth and eventually receive government transfers. Fewer than 5% of agents with a head age 85 or older receive such transfers.

Health Insurance

We use MEPS data to calibrate the co-insurance rate function $\psi()$. We use MEPS reports of out-of-pocket and total medical expenditures. In the model, we use estimates of the median co-insurance rate for each insurance plan. Insurance takes three value in MEPS public data: not insured, government insurance and private health insurance. We assume all respondents age 65+ with government insurance are on Medicare and that prior to age 65 those with government insurance are on Medicaid. We use medians because they are less affected by outliers. This yields a co-insurance rate of 1 for those without health insurance, 0.07 for those on Medicaid, 0.25 for those with employer plans and 0.2 for those age 65+ (on Medicare). The distribution of these co-insurance rates by insurance plan is given below.

Parameters	25th	median	75th	mean
No insurance	0.40	1	1	0.72
Medicaid	0.01	0.07	0.35	0.23
Private	0.11	0.25	0.48	0.33
Medicare	0.06	0.20	0.48	0.312

”For Online Publication” Appendix B Micro Data

Panel Study of Income Dynamics

We use the PSID version created by the Cornell Equivalent File Project (CNEF).¹³ These files include consistent variables for the years 1980 to 2005. The PSID interviews are done each year up to 1997 and every two years afterwards. We keep male agent heads and drop respondents from the oversample of low-income agents. We keep ages 21 to 99. Some of the analysis further restricts the sample. Sample weights are used whenever possible in order to make the sample representative. We also use the wealth surveys of 1984, 1989, 1994, 1999, 2001, 2003 and 2005. This data is obtained directly from PSID. Finally, additional information on labor force status, pension income and health insurance status is obtained from the individual and family files from the PSID. A total of 71,375 observations are available across all years with an average of approximately 3000 per year. A total of 7206 agent heads are followed over time with 16,5% of those followed for 22 waves. Below is information on the variables used in the analysis.

Wealth

We use the variable SX17, which is the sum of values of seven asset types, net of debt value plus home equity (X refers to wave). Values above \$1e6 are recoded as missing. Wealth is converted to 2005 dollars using the CPI.

¹³The files can be obtained at the CNEF homepage

Earnings

We use the variable i11110 from the CNEF. Earnings set to missing if above \$250,000 or below \$5,000 or if hours worked are too low or too high. We convert earnings to 2005 dollars using the CPI.

Other Income

We set other income to the sum of spousal earnings plus the sum of agent private pension and annuity income. We exclude values above \$250,000. We convert to 2005 dollars using the CPI.

Health

We use self-reported health from the CNEF. This variable is available from 1984 to 2005 on a scale going from 1 (excellent) to 5 (poor). We create three categories (poor-fair, good, very good-excellent).

Household Composition

We use the number of members of the household.

Education

Education is used as an instrument for estimating the equation for other income. It is defined as a 0/1 variable equal to one if the respondent has a college degree.

Birth Year

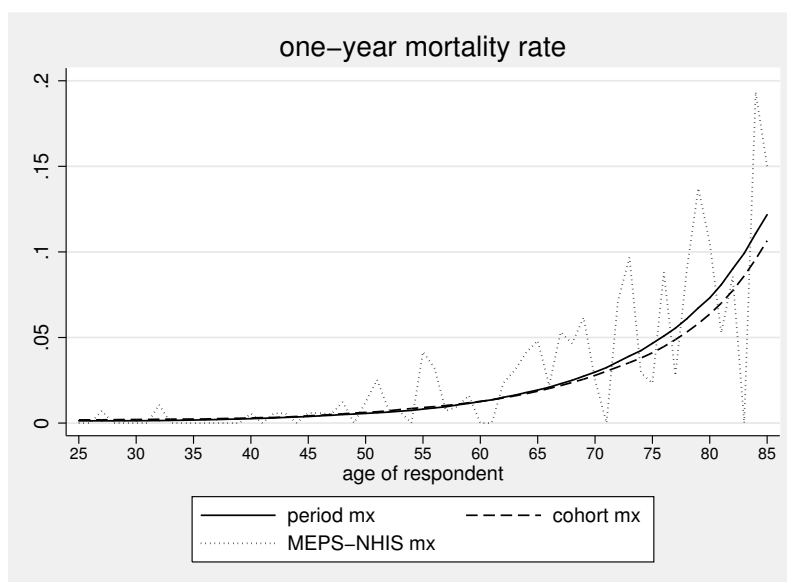
Birth year is recoded in 6 groups: earlier than 1925, 1926-1934, 1935-1944, 1945-1954, 1955-1964 and after 1966. The reference group in the various analysis we run is 1935-1944.

Medical Expenditure Panel Study

We use data from years 2000 to 2004 from the Medical Expenditure Panel Study (MEPS). We use data from the agent component full year consolidated data files. We select male respondents age 25 to 85 for the analysis. The MEPS interviews respondents over a 2 year span. Each panel, initially drawn from the National Health Interview Survey (NHIS) is surveyed 5 times. One panel starts each year. A total of 75,462 person-year were collected between 2000 and 2004.

Mortality

The MEPS indicator for mortality leads to an underestimate of mortality. But MEPS respondents are drawn from the NHIS. The NHIS has linked records of respondents with National Death Records for years 1985 to 2006. Hence, we link the MEPS record to the mortality follow-up conducted in MEPS. We then define mortality as occurring if the respondent died within the year following his interview. To validate the quality of mortality data, we merge these records period with period life tables for males by year and age (obtained from the Human Mortality Database) as well as cohort mortality rates for those born in 1940 from the Social Security Administration. The next figure shows the close correspondence although the small sample size beyond age 75 yields very volatile mortality rates. There is also some underestimation at older ages, probably due to the non-follow up of the institutionalized population in MEPS. But overall, the aggregate one-year mortality rate in the age range 25 to 85 is 0.012 in the MEPS-NHIS dataset while it is 0.013 according to period life-table. There is little difference in cohort and period mortality rates until age 70. Period mortality rates are larger than cohort mortality rates after this age.



Total Medical Expenditures

We use MEPS for the total medical expenditures over the calendar year using the CPI in 2005 dollars. We make three adjustments to this variable. First, we scale it up to the level of per capita personal health care spending from the National Health Expenditures (NHE) report for the years 2000 to 2004. MEPS surveys the non-institutionalized population. Hence, at older ages it is likely to underestimate medical expenditures. Cutler and Meara (2004) computed the adjustment factor to correct for this bias in MEPS. As a result, medical expenditures for the age 75+ group are bumped up by 8%. Finally we censor medical expenditures at \$50,000 to limit the influence of outliers.

Other Variables

Household income is taken from the household component of the MEPS data files. Obesity is defined as a body-mass index of more than 30. A variable indicating whether the respondent ever smoked is also constructed and used as control.

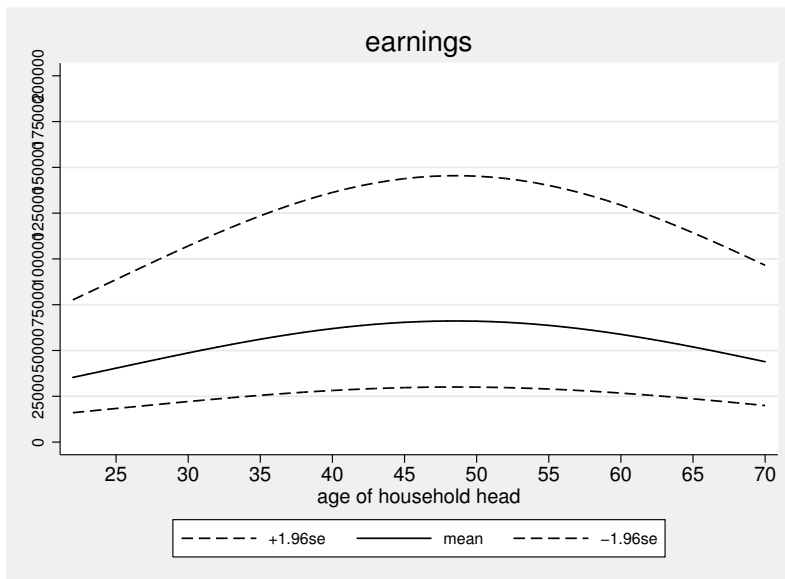
”For Online Publication” Appendix C Estimation of Auxiliary Processes

Earnings

We select PSID men aged 25 to 70 working full-time between 1994 and 1997 (2-year gap between waves after 1997). We have 42,764 person-years. The specification for annual real gross earnings of the household head is given by

$$E[\log y_{it}^e | \pi_{i0}, t] = \pi_{i0} + \pi_1 t + \pi_2 t^2$$

where the earnings shocks for the individual i $\eta_{it} = \log y_{it}^e - E[\log y_{it}^e | \pi_{i0}, t]$ follows an AR(1) process $\eta_{it} = \rho \eta_{it-1} + \varepsilon_{it}$, $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$. We first estimate parameters π_1, π_2 by fixed effect regression (within estimator). We set the constant term to the average of the fixed effect for those born between 1935 and 1945. Earnings peak around the age of 49 years old. We then use the residuals (including the fixed effects) to estimate the covariance parameters $(\rho, \sigma_\varepsilon)$ by minimum distance. The covariance parameter estimates are $\hat{\rho} = 0.973$ and $\hat{\sigma}_\varepsilon^2 = 0.008$. Hence, earnings shocks are quite persistent. The following figure reports the average earnings profile along with the 95% confidence interval using the unconditional variance of η_{it} .



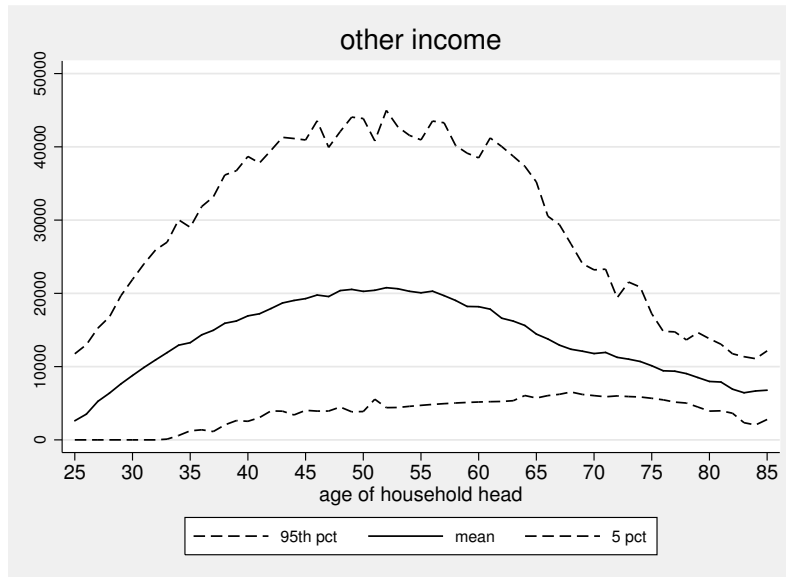
Other Income

We select PSID respondents from all waves, age 25 and over. We define other income as the sum of private pension income, spouse earnings and spouse Social Security benefits. We define the income of the household head, y_{it}^h , as his earnings plus his social security benefits. The econometric model is

$$y_{it}^o = \pi_3 + \pi_4 y_{it}^h + \pi_5 t + \pi_6 t^2 + \lambda_c + \varepsilon_{it}$$

where λ_c denotes cohort dummies. We instrument income of the household head y_{it}^h with education (a dummy for a college educated head) as in French (2005). We use the predicted profile of a household head born between 1935 and 1945. The following table gives the parameter estimates. The profile is hump-shaped and there is a moderate correlation between income of the household head and other income. Using actual income of the household head in the PSID panel, we also plot the distribution of predicted other income by age.

Parameters	Estimates	Std. Error
π_3	-26109**	1224.1
π_5	990.6**	51.6
π_6	-7.822**	0.497
π_4	0.306**	0.009
Obs.	65008	



Initial Distribution of State Variables

We select male household heads aged 24 to 28 (to boost sample size). There are minor cohort differences in initial real earnings, health and assets. We neglect those. The initial insurance coverage state is missing in PSID. For that, we use RAND HRS respondents aged 50 to 55 and born between 1935 and 1945 to estimate the extent of employer-tied and retiree coverage. We estimate that 20% of respondents do not have employer provided insurance, 40.1% have employer-tied coverage and 39.9% have retiree coverage. We use those estimates to draw initial health insurance coverage. By construction, there is no correlation between other initial state variables and insurance state. The initial sample size is 2,500 respondents.

We duplicate each observation and then take a sample with replacement of size 5,000. Initial earnings are used to initialize the error term η_{25} . Since we do not have data on ame_{25} , we fix it to zero.

”For Online Publication” Appendix D Estimation of Health Processes

We use MEPS to estimate health and mortality processes. We use data on males aged 25 to 85.

Health

Let $h_{it+1} = j$ be the health status at age $t + 1$, $j = 1, 2, 3$. Current health status is $h_{it} = k, k = 1, 2, 3$. We specify the following dynamic multinomial model with controls for risk factors, x_{it} (smoking and obesity status) where

$$\Pr(h_{it+1} = j | h_{it} = k, t, m_{it}, x_{it}) = \frac{e^{\delta_{0jk} + \delta_{1j}t + \delta_{2j} \log m_{it} + \delta_{3j} \log m_{it}^2 + x_{it}\delta_{4j}}}{\sum_{j'} e^{\delta_{0j'k} + \delta_{1j'}t + \delta_{2j'} \log m_{it} + \delta_{3j'} \log m_{it}^2 + x_{it}\delta_{4j'}}$$

We normalize parameters of health state $j = 1$ to zero. One might be worried that m_{it} is endogenous. The vector x_{it} is included in the specification we estimate as control variables. It includes an indicator for ever smoking and one for obesity (BMI>30), which alleviates some of the concerns with respect to common factors (such as socio-economic status) affecting both medical spending (and health. Current health state $h_{it} = k$ captures the history of the health process assuming it is Markovian. This also helps alleviate concerns about unobserved heterogeneity since we are comparing people with the same health status. However, there might be simultaneity if the current health shock increases medical spending. This would bias downward the effect of health spending on health. In fact, direct estimation reveals negative effects of medical spending on health.

We use a control function approach to correct for the simultaneity of m_{it} (Peltrin and

Train, 2010). At time t , determinants of medical spending that are uncorrelated with the health shock, conditional on h_{it} and x_{it} , are good candidates for instruments. Given the model, the log of current household income should be correlated with current medical spending but not with next year's health status. Hence, we first run the following regression

$$\log m_{it} = \varphi_1 + \sum_{k>1} \varphi_k I(h_{it} = k) + z_{it}\varphi_6 + x_{it}\varphi_7 + \varphi_8 t + \nu_{it}$$

where z_{it} is the log of household income. Results are presented in the next table. A partial F-test on the instruments yields a value that indicates the instruments are not weak.

Parameters	Estimate	Robust Std. Err.
φ_1 (constant)	1.542**	0.301
φ_2 (good)	-0.904**	0.137
φ_3 (>good)	-1.208**	0.130
φ_6 (log income)	0.124**	0.024
$\varphi_{7,1}$ (obese)	0.592**	0.098
$\varphi_{7,2}$ (smoking)	-0.152**	0.089
φ_8 (age)	0.081**	0.002
N	4686	
R-squared	0.183	
Partial-F log income	26.67	

We compute residuals $\hat{\nu}_{it}$, which we plug into the health process that becomes

$$\Pr(h_{it+1} = j | h_{it} = k, t, m_{it}, x_{it}, \hat{\nu}_{it}) = \frac{e^{\delta_{0jk} + \delta_{1j}t + \delta_{2j} \log m_{it} + \delta_{3j} \log m_{it}^2 + x_{it}\delta_{4j} + \hat{\nu}_{it}\delta_{5j}}}{\sum_{j'} e^{\delta_{0j'k} + \delta_{1j'}t + \delta_{2j'} \log m_{it} + \delta_{3j'} \log m_{it}^2 + x_{it}\delta_{4j'} + \hat{\nu}_{it}\delta_{5j'}}$$

Standard errors are computed by bootstrap to account for the estimation noise from estimating ν_{it} . We report the results of estimation by maximum likelihood in the following table. Health decreases with age; there is considerable state-dependence in health as revealed by the current health effects, particularly in good health states. Obesity and smoking are negatively correlated with health.

Parameters	Good		>Good	
	Par	Std.Err	Par	Std.Err
δ_0 (constant: <good)	-1.409	0.539	-3.054**	0.845
δ_0 (good)	2.695**	0.221	3.609**	0.334
δ_0 (>good)	3.219**	0.279	6.031**	0.421
δ_1 (age)	-0.053**	0.013	-0.109**	0.021
δ_2 ($\log m_{it}$)	0.712**	0.164	1.332**	0.252
δ_3 ($\log m_{it}^2$)	-0.027**	0.004	-0.045**	0.005
$\delta_{4,1}$ (obese)	-0.452**	0.139	-0.852**	0.193
$\delta_{4,2}$ (smoking)	-0.063	0.103	-0.111	0.126
δ_5 ($\hat{\nu}_{it}$)	-0.568**	0.164	-1.074**	0.257
N	4621			

The parameter estimates of δ_{5j} are jointly significantly different from zero which reveals that m_{it} is endogenous. The estimates reveal that health spending has a positive effect on health, increasing the likelihood of good health states.

Mortality

Mortality depends on age and health status and follows a Gompertz hazard function. The probability of death over a one-year interval is given by

$$\Pr(d_{it+1} = 1 | h_{it} = k, t) = 1 - \exp(-\exp(\delta_6 t) \exp(\delta_{7,k}))$$

Parameters are estimated by maximum likelihood. Parameter estimates are reported in the next table.

Parameters	Estimate	Std. Error
$\delta_{7,1}$ (constant)	-7.451**	0.543
$\delta_{7,2}$ (good)	-1.259**	0.257
$\delta_{7,3}$ (>good)	-1.765**	0.263
δ_6 (age)	0.069**	0.007
N	7,392	

There are two issues with the estimated mortality process. First, MEPS data is lacking at older ages. So we extrapolate from the process estimated at younger ages. Second, given the limited number of years, it was not possible to include cohort effects. But the model requires a cohort life-table for those born between 1935 and 1945. Hence, we use cohort mortality rates from Social Security to construct a correction factor such that average mortality rates computed from the health data are equal to the Social Security mortality rates.

”For Online Publication” Appendix E Solution Method and Estimation of Preference Parameters

Solution Method

Starting at the last age, which we set at $T = 110$, mortality is certain in the following period. Therefore, the agent consumes all resources left at that point. This means we know $V_T(s_T)$. Proceeding recursively, we discretize the continuous variables of the state-space with more points at lower values (assets and average indexed monthly earnings). We use 48 asset points and 24 AME points. To solve for optimal consumption and medical expenditures, we also use grid search with 24 points for each variable. We use bi-linear intrapolation for next period’s value function. For integration of earnings shocks, we follow the discrete approximation approach of Tauchen (1986) and use 9 points. Once we have solved for optimal decision rules, we simulate the life paths of 5,000 agents using draws of earnings, health, mortality and initial conditions from the data (described in the next section).

Construction of Moment Conditions

There are four sets of moment conditions. Each compares a statistic computed from the data to one computed from simulations. We first describe how we compute the statistics from the data.

First, we seek to construct a mean wealth profile by age from the PSID which is not contaminated by cohort effect and household composition. We follow French (2005) and

estimate a fixed effect regression with controls for household size and an unrestricted set of age dummies. We then construct the profile by using the average of the fixed effects for those born between 1935 and 1945 and a household size of 3.

Next, the average medical expenditures by age are computed from MEPS. Because of smaller sample size than for wealth, we opt for a regression which directly controls for birth year, household size and unrestricted age dummies. We then predict average medical expenditures for someone born between 1935 and 1945 with a household size of 3.

Labor force participation by age is predicted separately for those in poor-fair health and those with good and very good-excellent health. We use regressions which control for cohort effects and unrestricted age dummies. When predicting we set the cohort effects for someone born between 1935 and 1945.

Finally, we seek to match mortality rates for this cohort. We know from lifetables that there are significant cohort effects in mortality. We use cohort mortality rates for those born in 1940 from the Social Security Administration. This profile was also used to correct the mortality process described in Appendix D and was shown in Appendix B.

We compute standard errors for each moment by computing the deviation of (adjusted) respondent level data to the statistics computed above. We use the strategy outlined in French (2005) to deal with the unbalanced nature of the PSID and MEPS panels.

Estimator

Denote the j th moment condition involving the variable z by

$$\tilde{g}_j(\theta) = \frac{1}{N} \sum_{i \in n_j} \left(z_{i,j}(\theta_0) - \frac{1}{S} \sum_s \tilde{z}_{s,j}(\theta) \right)$$

where N denotes the combined sample size of PSID and MEPS used in estimating the moment vector, $z_{i,j}(\theta_0)$ the adjusted data of respondent i contributing to the moment condition (there are n_j such respondents) , and finally $\tilde{z}_{s,j}(\theta)$ simulated data from draw s of shocks (earnings and health). S denotes the number of simulations. The data is by assumption

generated from the model at the true value of the parameters θ_0 . Stacking these moment conditions, we obtain a vector $\tilde{g}_N(\theta)$ which has expectation zero at $\theta = \theta_0$. The Method of Simulated Moment (MSM) estimator is given by

$$\hat{\theta}_{MSM} = \arg \min_{\theta} \frac{N}{1 + \tau} \tilde{g}_N(\theta)' W_N \tilde{g}_N(\theta)$$

where W_N is the inverse of the covariance matrix of the data and $\tau = N/S$. Given some regularity conditions, the MSM estimator is consistent for θ_0 for fixed S when N goes to infinity. It is also asymptotically normal. An estimate of the variance matrix of the estimates is given by

$$V(\theta_{MSM}) = (1 + \tau) (G_N' W_N G_N)^{-1}$$

where G_N is the matrix of derivatives of the moment vector with respect to the parameters. If the model is correctly specified the value of the objective function is distributed as a χ^2 random variable with $J - K$ degrees of freedom where J denotes the number of moments and K denotes the number of parameters to be estimated.

Since the objective function is generally not smooth and has local minima, we use the Nelder-Mead algorithm to find the minimum.

Figures

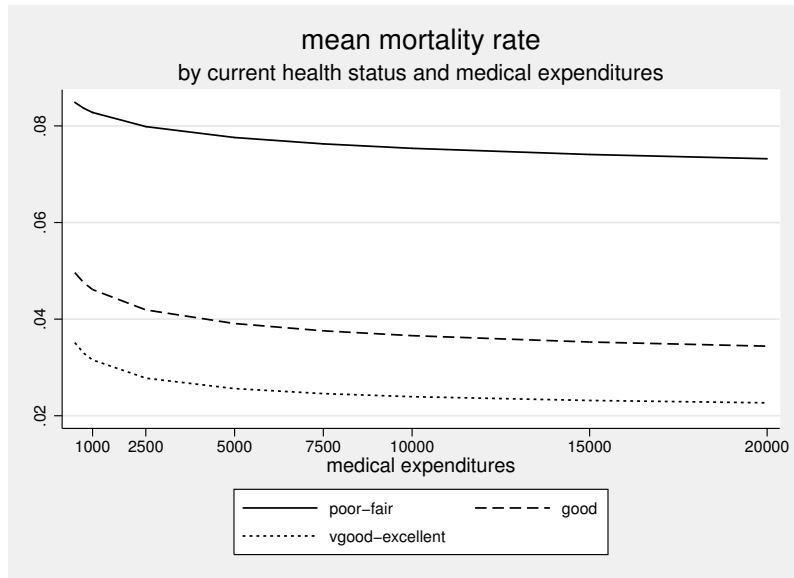


Figure 1: **Mortality Rates by Current Health Status and Level of Medical Expenditures, Age 65+**: Effects are obtained by combining the marginal effects from the health process weighted by the conditional mortality probabilities by health status and averaged over the population age 65+.

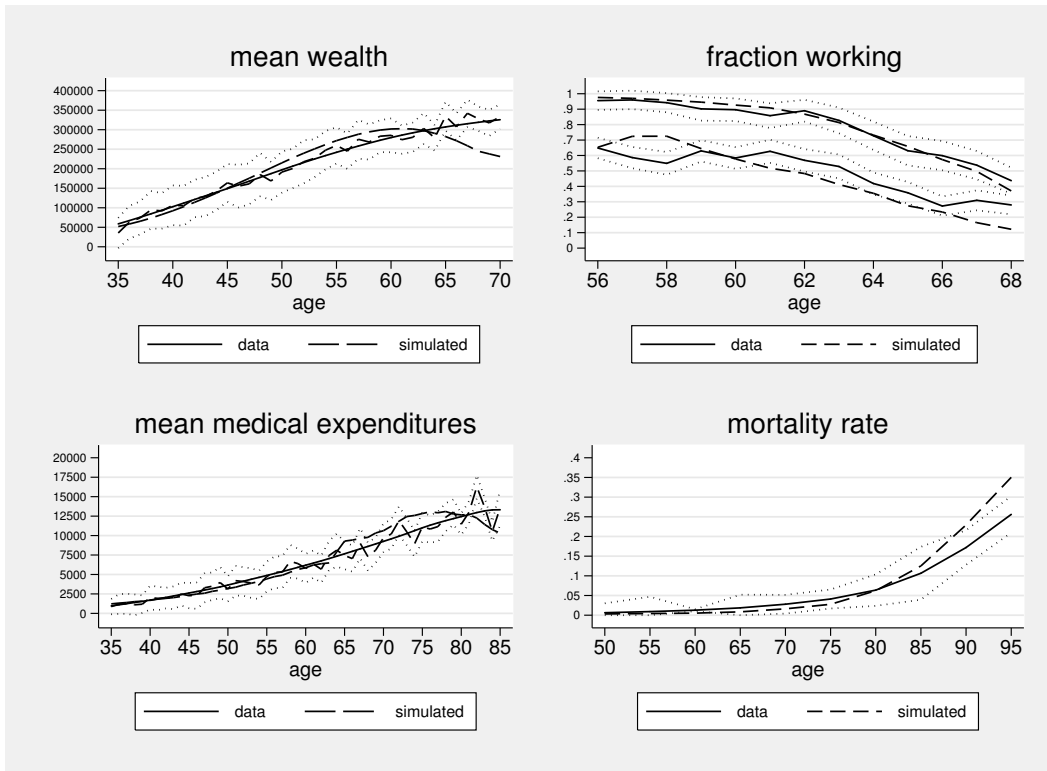


Figure 2: **Age Profiles from Data and Simulations:** The solid lines show the average profile from the data; 95% confidence intervals of the data are shown by dotted lines. The dashed lines show the simulated profiles. In the top right panel, the fraction working by age is shown for those in very good or excellent health (higher profile) and in poor or fair health (lower profile).

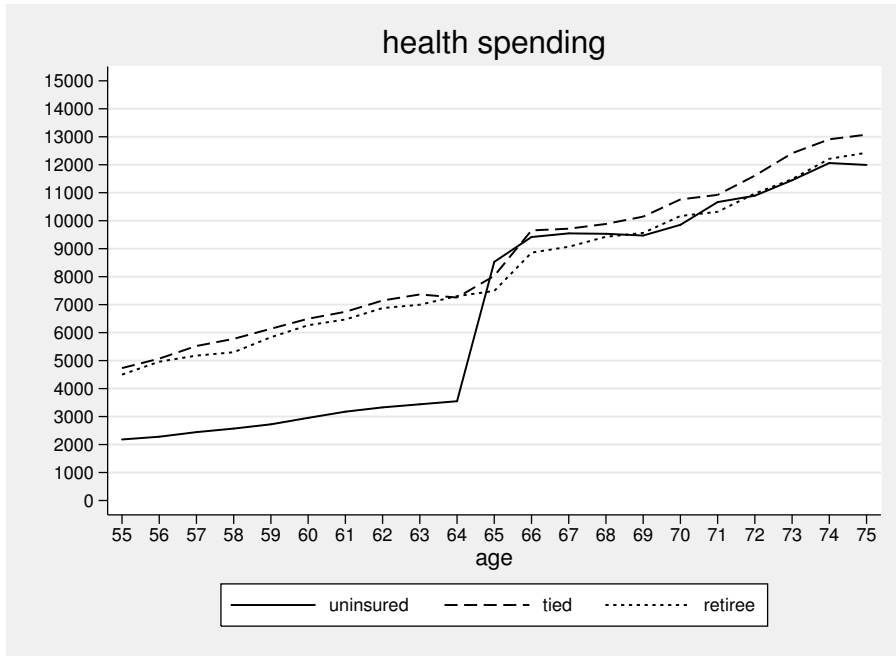


Figure 3: **Health Spending by Age and Insurance Status:** Average medical expenditures are computed from simulated data and stratified by insurance status prior to Medicare eligibility.

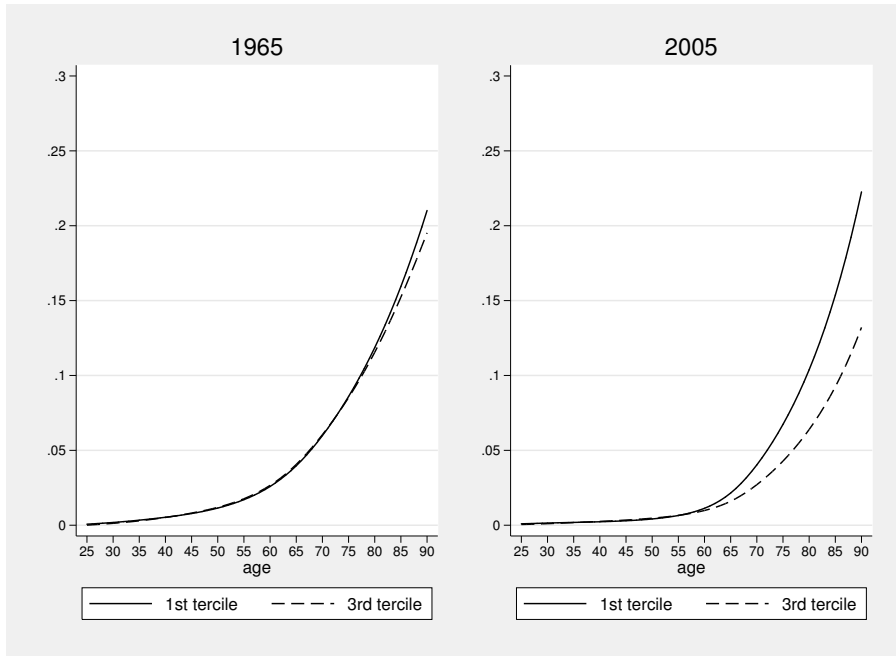


Figure 4: **Mortality Rates by Age and Income Tertile 1965 and 2005:** We plot simulated mortality rates by starting income tertile (age 25) from the 1965 scenario and the 2005 scenario. The mortality rate profiles are smoothed using a lowess filter.

Tables

Parameter	Point Estimate	Std. Error
σ	3.365	0.958
γ	0.436	0.005
ϕ_1	696.1	708.3
ϕ_2	371.6	442.3
β	0.983	0.036
α_2	0.190	0.149
α_3	0.219	0.047
S	5,000	
N	10,848	
#moments	50	
OIV (df=43)	164.8	

Table 1: **Preference Parameter Estimates by Method of Simulated Moments:** Standard errors computed at the solution using the formula shown in Appendix E. S refers to the number of simulated individuals while N is the number of different respondents used in estimating the profiles from the data. The overidentification test value is given by the value of the objective function of the MSM estimator at the minimum and is distributed as a chi-square with 43 degrees of freedom.

Parameter	No Controls	Controls	Fixed Effects
log(Income)	0.592** (0.002)	0.538** (0.004)	0.513** (0.003)
log(co-insurance)	-0.555** (0.002)	-0.570** (0.001)	
Obs	122,778	117,778	117,778
R-squared	0.835	0.957	0.934

Table 2: **Income and Co-insurance Elasticities of Health Care Spending in Base-line Simulations:** Standard errors are calculated using clustering at the respondent level. The first specification includes age dummies (5-year intervals). The second adds health status and assets. The last specification uses the within fixed effect estimator. Prior to age 50, insurance status does not vary within respondent. Hence, co-insurance is excluded from the fixed effect specification. ** denotes $p < 0.05$.

Outcome	1965	Income	Insurance	Technology	Other	2005
Avg. total medical exp.	569.1	771.7	929.2	1972.5	593.1	5257.2
Avg. oop exp.	386.4	519.9	303.9	933.2	404.6	1330.3
life expectancy	69.8	70.3	70.1	79.4	64.9	78.1
e_{50}	24.0	24.1	24.1	31.9	20.5	31.3
CV 1965 (%)	-	26.7%	3.3%	64.3%		75.5%

Table 3: **Simulation Scenario Results 1965-2005**: Results in the first column pertain to the 1965 environment. The second column implements the 2005 income scenario keeping insurance and technology at their 1965 level. The third column implements the 2005 insurance scenario keeping 1965 income and technology. The fourth column implements the 2005 technology scenario keeping income and insurance at their 1965 level. The fifth column implements the increase in mortality due to other factors (notably smoking and obesity). Finally, the last column reports results for the baseline scenario in 2005. Remaining life expectancy at age 50 is reported as e_{50} . The last line computes the fraction of consumption in each scenario which would need to be taken away from consumers such that they enjoy the same welfare at age 25 as in the 1965 environment (measure of compensating variation CV).

Outcome (% total)	Income	Insurance	Technology	Other	Complementarity
Medical spending	4.3	7.7	29.9	0.5	57.3
Life expectancy	6.0	3.6	115.7	-59.0	33.7

Table 4: **Contribution to Growth in Medical Spending and Longevity 1965-2005:** The first column implements the 2005 income scenario keeping insurance and technology at their 1965 level. The second column implements the 2005 insurance scenario keeping 1965 income and technology. The third column implements the 2005 technology scenario keeping income and insurance at their 1965 level. The fourth column implements other changes to mortality during the period (notably obesity and smoking), keeping everything else unchanged. The last column reports the residual growth which can be interpreted as a complementarity effect between scenarios.

		Baseline		Expansion	
health spending					
	age	Uninsured	Tied	Uninsured	Tied
	60-64	\$ 3,293.7	\$ 6,973.4	\$ 6,892.5	\$ 6,802.8
	65-75	\$ 10,130.3	\$ 10,532.4	\$ 10,108.8	\$ 9,976.8
health excellent					
	age	Uninsured	Tied	Uninsured	Tied
	60-64	0.804	0.874	0.879	0.884
	65-75	0.786	0.791	0.803	0.793
working					
	age	Uninsured	Tied	Uninsured	Tied
	60-64	0.834	0.910	0.862	0.859
	65-69	0.284	0.283	0.288	0.278

Table 5: **Expansion of Insurance prior to Medicare Eligibility:** Simulated outcomes in the baseline, and in the insurance expansion scenario which provides the uninsured with the same plan as that of workers with employer provided health insurance.