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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 36.3% of the rise in health spending (technology 31.5% and insurance 4.8%), while income explains only 4.4%. By simultaneously occurring over this period, these changes may have led to complementarity effects which explain an additional 59% 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 1.7%, explains almost all of the rise in life expectancy at age 25 over this period. Welfare gains are substantial and most of the gain appears to be due to technological change (47% out of a total gain of 67%).

JEL Classification: I10, I38, J26

Keywords: health spending, longevity, life-cycle models, technological change

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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]

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 at 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

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

the way patients are treated. Skinner and Staiger (2015) 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.

Technological progress may therefore lead to 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. 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 (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). 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 67% 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.

A number of recent papers also feature endogeneous 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 exogeneous to health investments. In order to simultaneously model health spending and survival, our model explicitly endogenizes the effect of health spending on survival. Macro models such as Suen (2005) are calibrated and focus on representative agents. Instead, we estimate preferences and technology, using micro-data, which allows us to quantify the sources of growth in spending and longevity. Hugonnier et al. (2013) and Pelgrin and St-Amour (2016) estimate models of health investments using micro-data. In this paper, we allow for a rich environment which features detailed Social Security rules along with a retirement decision (Social security claiming and labor force participation). 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 concludes.

2 Stylized Model

Consider the stylized model of Hall and Jones (2007). The agent receives a constant income y and chooses how to allocate it between consumption c and health expenditures m. His life expectancy $L(z, m)$ increases with health spending m, is strictly concave in m, and depends on a technology parameter z. The agent derives utility $u(c)$ from consumption c, where utility is strictly concave in c. Lifetime utility is the product of length of life and period

[2] Other 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 exogeneous to health investments. Yogo (2009) 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.

utility, $v(m,z,y) = L(z,m)u(y-m)$ (see Hall and Jones, 2007).

The agent's problem is to maximize $v(m,z,y)$ with respect to m. Optimal health expenditures $m^*(z,y)$ satisfy the first-order condition (FOC), $L_m(z,m)u(y-m) = L(z,m)u_c(y-m)$, which equates the marginal benefit of life extension (left-hand side), consisting of years of utility gained, with its marginal cost (right-hand side), consisting of utility lost from lower consumption $y-m$, due to higher expenditures $m^*(z,y)$.

Taking the derivative of the FOC with respect to income y and technology z, we obtain

$$\frac{\partial m^*}{\partial y} = \frac{L_m(z,m^*)u_c(y-m^*) - L(z,m^*)u_{cc}(y-m^*)}{2L_m(z,m^*)u_c(y-m^*) - L(z,m^*)u_{cc}(y-m^*) - L_{mm}(z,m^*)u(y-m^*)}$$

$$\frac{\partial m^*}{\partial z} = \frac{L_{mz}(z,m^*)u(y-m^*) - L_z(z,m^*)u_c(y-m^*)}{2L_m(z,m^*)u_c(y-m^*) - L(z,m^*)u_{cc}(y-m^*) - L_{mm}(z,m^*)u(y-m^*)}.$$

The direct effect of income y (see numerator) is to increase the marginal benefit and to decrease the marginal cost of health expenditures m. Hence $\partial m^*/\partial y > 0$.[3]

Whether technology z increases health spending m is less obvious. If health expenditures are more efficient through better technology it may be optimal to spend less and consume more. Since longevity increases in technology z, the direct effect of z (see numerator) is to increase the marginal cost of health expenditures m. Only if technology reinforces health spending in extending life, i.e. $L_{mz}(z,m^*) > 0$, to such an extent that it increases the marginal benefit of health expenditures more than its marginal cost, i.e. $L_{mz}(z,m^*)u(y-m^*) > L_z(z,m^*)u_c(y-m^*)$, will technology increase health spending $m^*(z,y)$. As discussed, there are many reasons to believe that some of the improvements that occurred suggest $L_{mz}(z,m) > 0$. However, this effect must be large enough to yield increased spending.

A simple calibration exercise shows that complementarity effects (such as between income and technology in health spending) can be important. Life expectancy at birth in the US rose from 70.4 to 77.7 years between 1965 and 2005 (Human Mortality Database [HMD]) and average personal health spending from \$570 to \$5,738 (in 2005 dollars; National Health

[3]The denominators in both expressions are identical and positive for increasing and strictly concave utility $u(c)$ and life extension $L(z,m)$ functions. It can also be shown that $\partial c^*/\partial y > 0$ so that higher income is used both to extend life and increase utility.

Expenditure Accounts [NHEA] data). To illustrate, 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, $L(z, m) = L_{min} + z \log(m)$.

Although $L_{mz}(z, m) = 1/m > 0$ implies technology and income are complements, whether technology increases spending will depend on parameter values. For the simple functional forms assumed one can derive the condition for which $\partial^2 m^*/\partial z \partial y = \partial^2 m^*/\partial y \partial z > 0$ (see equation 19 in Appendix A). We calibrate parameter values to match the rise in longevity and health spending over the period 1965-2005.[4] These values are consistent with the condition for $\partial^2 m^*/\partial z \partial y = \partial^2 m^*/\partial y \partial z > 0$ for both the 1965 and 2005 income and health spending data. Thus complementarity in income and technology should lead to a total effect that is larger than the sum of the separate contributions of improvements in technology and increases in income.

With 1965 technology we can solve for optimal health expenditures given income in 2005. Health expenditures increase by \$3,108. In a second counterfactual, we keep income constant at its 1965 level and bring the technology to its 2005 level. Optimal health 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 health expenditures over the period. The difference is due to a complementarity effect: an additional \$1,860 increase in health spending arises from technology and income improving concurrently. Optimal health 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 health expenditures are not constant over the life cycle. They increase

[4] We 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 health 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 $\sigma = 1.424$.

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 be other 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 $\{1 = \text{poor or fair}, 2 = \text{good}, 3 = \text{very good or excellent}\}$.[5] 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. The agent can choose whether or not to participate in the

[5] In principle, one could consider multiple dimensions of health. Other health measures in our data include more objective measures such as the number of medical conditions, or limitations in activities of daily living. As will become clear when discussing the estimation of the model, only self-reported health is available for the different inputs required by the model and modeling many dimensions of health renders the model almost unsolvable. Self-reported health is commonly used in life-cycle models of labor supply and savings (e.g., French, 2005).

labor market ($q_t = 1$ if working, $q_t = 0$ if not).[6] 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 120.[7] 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 loose 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. [8]

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

[6] We do not model hours of work for two reasons. First, differences in hours of work by health are small conditional on working for males. Differences in participation are much larger. Second, this would introduce a third continuous decision variable and add considerable computational burden.

[7] The maximum age is set at 120 for computational reasons. Solutions to the model are insensitive to this choice for higher maximum ages.

[8] We do not model the decision to move to a nursing home and associated expenditures. Those expenditures are of a different nature than medical expenditures affecting both health and life expectancy. This is also consistent with the data we use which does not include the institutionalized. LTC spending did not grow faster than other health spending over the period we cover. According to National Health Expenditures Accounts (NHEA), LTC spending represented 3.3% of total health spending in 1965 compared to 5.4% in 2005.

utility function

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

where L is the maximum annual amount of leisure available (set to 4000 hours), and $\varsigma_q = 2000$ is the number of hours worked when working full-time ($q_t = 1$). The parameter α_h is the baseline utility level in health state h_t which governs the utility benefit of living longer. 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. Following French (2005), the agent derives utility from leaving wealth w_t to heirs if he dies at age t which is represented by a bequest function given by

$$b(w_t) = \xi \frac{(w_t + K)^{\gamma(1-\sigma)}}{1-\sigma} \tag{2}$$

where we fix K = \$500,000 as in French (2005). Hence, ξ measures the strenght of the bequest motive. For ease of reference, collect the preference parameters to be estimated in the vector $\theta = (\alpha_1, \alpha_2, \alpha_3, \gamma, \phi_1, \phi_2, \sigma, \beta, \xi)$.

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

$$y_t = \tau_n(y_t^e, y_t^o, y_t^{ss}, rw_t) \tag{3}$$

The net income function, τ_n, takes account of Federal taxes as well as Social Security and Medicare contributions (see Appendix B for details).

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

$$x_t = w_t + y_t. \tag{4}$$

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

$$tr_t = \max(0, x_{min} - x_t) \tag{5}$$

Out-of-pocket medical expenditures are given by

$$oop_t = \psi(f_t, t, tr_t)m_t \tag{6}$$

where the co-insurance rate, ψ, depends on insurance coverage f_t, age t and transfer receipt tr_t. 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.[9]

The resource constraint is completed with the equation for wealth accumulation. Agents cannot end the period with negative private wealth. Wealth at the end of the period is given by

$$w_{t+1} = x_t + tr_t - c_t - oop_t \tag{7}$$

with $w_{t+1} \geq 0$. The earnings process is quadratic in age and features an AR(1) error

[9] We did not allow for a deductible and co-insurance rate structure. Deductibles are heterogeneous, not available in the data, and we cannot construct them on the basis of available data, such as total and out-of-pocket medical expenditures. Hence, a two-part pricing schedule cannot be implemented.

structure:

$$\log y_t^e = \pi_0 + \pi_1 t + \pi_2 t^2 + \eta_t \tag{8}$$

where the earnings shock is given by $\eta_t = \rho\eta_{t-1} + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.[10]

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.[11] 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. The Social Security system he faces was shaped almost entirely by the 1983 Social Security reform.[12]

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 are found in Appendix B.

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

[10] In principle, earnings could depend on health status. However that effect likely occurs through labor supply rather than wages (Currie and Madrian, 1997). Since workers choose labor supply, (lifetime and current) earnings will effectively depend on health. Fixed effect regressions of earnings on health in the data we use reveal non-statistically significant effects of health on earnings (results available upon request).

[11] In principle, the model could account for changes in family composition over time and decisions within the household which are important for capturing life-cycle decisions (see for example Lise and Seitz, 2011). Michaud and van Soest (2008) estimate causal feedback effects between the health of both spouses and wealth. However, the computational burden imposed by modelling individual decisions and outcomes within households are too great to make this feasible in our setting.

[12] An alternative would be to build on changes over time in tax and pension rules. Assuming agents anticipated these would not create a drastically different world than what is assumed here since the important decisions agents make occur after age 50. 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).

health transitions

$$\Pr(h_{t+1} = j | h_t = k, t, m_t) = \frac{e^{\delta_{0jk} + \delta_{1j} t + \delta_{2j} \log m_t + \delta_{3j} \log m_t^2}}{\sum_{j'} e^{\delta_{0j'k} + \delta_{1j'} t + \delta_{2j'} \log m_t + \delta_{3j'} \log m_t^2}}. \tag{9}$$

where $j = 1$ is the base category (fair or poor health).[13] 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 is also a function of age, $\delta_{1,j}$, which captures changes in health over the life-cycle independent of how much is spent on health. This health-production function is consistent with the view that health is a stock which depreciates over time (depends on age) 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

$$p_{d_{h,t}} = \Pr(d_{t+1} = 1 | h_{t+1} = k, t) = 1 - e^{-e^{\delta_6 t} e^{\delta_{7,k}}}. \tag{10}$$

Thus mortality depends indirectly on medical expenditures through their effect on health status. The endogenous nature of medical care is an important and distinct feature of our model as other papers, such as DeNardi, French and Jones (2010), typically assume that medical spending does not affect future health.

3.5 Maximization Problem

Denote the state space at age t as $s_t = (h_t, \eta_t, ss_t, f_t, ame_t, w_t)$. Subject to the law of motion for wealth in equation 7 and the transition probabilities for earnings, health and mortality (equations 8, 9 and 10), the agent's maximization problem can be written as a Bellman

[13] We use $\log(1 + m_t)$ instead of $\log(m_t)$ so that the production function is defined for $m_t = 0$.

equation

$$V_t(s_t) = \max_{c_t, m_t, q_t, ss_{t+1}} u(c_t, h_t, q_t) + \beta \sum_h (1 - p_{d_{h,t}}) p_{h,t} E_{\eta_{t+1}} V_{t+1}(s_{t+1}) \tag{11}$$

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 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 F.

4 Data and Estimation

We focus on males in order to avoid dealing with career interruptions and important changes to female labor supply over the period. 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 2005 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 C.

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 and obtain measures of total medical expenditures. 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}. Data on medical expenditures include the cost of medical visits, inpatient, outpatient as well as drug expenditures. It does not include nursing home expenditures. Since nursing home expenditures are conceptually closer to consumption than to investment in health, this omission is consistent with the model. The MEPS dataset is also used to estimate the co-insurance rates, $\psi()$. Details on sample selection and the construction of variables used in MEPS are given in Appendix C.[14]

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 estimator. Earnings are hump-shaped and peak around age 49 years. The estimate of the autocorrelation coefficient ρ is 0.953 and the variance of the innovation is $\sigma_\varepsilon^2 = 0.024$ (see Appendix D for details on the estimation). The "other income" process is estimated by instrumental variables using education as an instrument for measurement error (French, 2005). "Other income" is also hump-shaped, with a peak at age 51. A ten dollar change in earnings and Social Security benefits of the agent head translates into a \$3.25 change in other income. We report more details in Appendix D.

[14]Both 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.

4.1.2 Health and Mortality

Estimating directly the production function for health may lead to biased estimates. Indeed, estimating parameters by multinomial logit yields a negative effect of medical expenditures on health. One concern is 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 (reverse causality). 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).[15] As detailed in Appendix E, we use a control function approach (Petrin and Train, 2010). In this context, a valid exclusion restriction is a variable 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 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. We illustrate in Figure 1 the exact timing of the variables. We first estimate an equation for the log of medical expenditures given current health, risk factors and the log of past income. The estimated income elasticity is 0.151 and is highly statistically significant (partial F=106.22). 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 estimates 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 very good or excellent health in the next period by 6.5 percentage points at $5,000 of spending (22%

[15] We 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.

are in very good or excellent health in the estimation sample). Since the effect of medical expenditures on health is quadratic in $\log(m)$, there may be a point above which medical expenditures have a negative effect on health. However, given the estimates, the level of spending above which medical spending increases the probability of being in poor health is \$1.73 million. Hence, this is unlikely to occur when solving the model. Estimation results are reported in Appendix E.[16]

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 2 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 \$13,735 which is the average welfare transfer over this period according to the Welfare Benefit Database (`http://www.econ2.jhu.edu/people/moffitt/datasets.html`). 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 B provides details on the construction of these shares and other institutional parameters.

[16] When solving and simulating from the model we use the cohort-age average value for obesity and smoking rather than individual level data. Allowing for additional state variables that track these behaviors would be computationally prohibitive.

4.2 Preference Parameters

The remaining parameters to estimate are $\theta = (\alpha_1, \alpha_2, \alpha_3, \gamma, \phi_1, \phi_2, \sigma, \beta, \xi)$. 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 at each age between ages 35 and 84; average medical expenditures at each age between ages 35 and 84; proportion of individuals working, by health status, at each age from 35 to 69 (agents cannot work beyond 70 in the model) and mortality from Social Security mortality tables from ages 35 to 84. These profiles are constructed using the methodology outlined in French (2005) and accounting for cohort effects. Appendix F gives details on the construction of each profile.

The wealth profile primarily provides information on σ, β and ξ 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 $(\alpha_1, \alpha_2, \alpha_3)$ given that the health process is estimated in the first step. The mortality profile provides an overidentifying restriction that allows to test whether our mapping between medical spending and health is well specified.

We have 254 moments for 9 parameters. We use the inverse of the covariance matrix of the adjusted data from PSID and MEPS as the optimal weighting matrix for the MSM estimator. More details on the properties of the estimator are found in Appendix F. [17]

[17] Since 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. Similarly, for ϕ_1 and ϕ_2 we rescale as $\phi_j^* = \phi_j(L - \varsigma_p)$. Hence, ϕ_j is interpreted as the fraction of residual leisure, when working, which is lost due to health state j relative to very good/excellent health.

4.2.1 Estimation Results

The first column of Table 1 reports baseline parameter estimates along with standard errors. We obtain an estimate for the general curvature of the utility function, $\widehat{\sigma} = 3.3824$ (se = 0.5795). Given our estimate of the consumption share in the utility function, $\widehat{\gamma} = 0.6507$ ($se = 0.005$), we obtain the coefficient of risk aversion, keeping labor supply fixed, as $-(\widehat{\gamma}(1-\widehat{\sigma})-1) = 2.55$ (French, 2005). We estimate that agents are patient, with a discount factor estimate of $\widehat{\beta} = 0.9598$ ($se = 0.0054$) which given $R = 1.04$ yields $R\beta \approx 1$. This estimate is 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 fraction of residual leisure time lost when in poorer health are $\widehat{\phi}_2 = 0.4803$ ($se = 0.0603$) and $\widehat{\phi}_1 = 0.7826$ ($se = 0.0259$). Estimates of α_1, α_2 and α_3 are respectively -0.1705 ($se = 0.1117$), 0.7625 ($se = 0.1801$) and -0.4003 ($se = 0.1659$), the latter two being statistically significant from zero. Overall, once combined with the leisure penalty for bad health, utility increases with health, which has an impact on the desire of agents to invest in health. Finally, we estimate a sizeable bequest motive with an estimate of $\xi = 1.1067$ ($se = 0.6119$), statistically significant at the 10% level. Using a specification of utility and bequest motive similar to ours, French (2005) estimates a parameter of 1.69, a value we cannot reject statistically.

4.2.2 Model Fit

The baseline specification of the model fits the data well given that we only have 9 preference parameters and none of these parameters depend on age. The Chi-square statistic for overidentifying restrictions gives a value of 172.78 while the critical value at a 5% level is 210.7. Inspection of the simulated profiles in Figure 3 shows a relatively close fit. The simulated moments are for the most part within the confidence intervals of the moments estimated from the data. One exception is labor force participation of those in very good health (green line), which are higher in the simulated profiles than in the data. One possibility for this departure is that we did not model private defined-benefit pensions, which may provide an incentive to stop work early, in particular for those in good and in very good health. The model is able to capture the overall patterns of declining labor force participation without any direct dependence of utility on age.

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 ask, it is worth investigating the elasticities the model generates. To this end, we use simulated data generated by the model. We first assess how medical expenditures vary with the co-insurance rate. We assume all individuals face the same co-insurance rate, independent of insurance coverage. We vary this co-insurance rate with values 0.25, 0.5, 0.75 and 0.95. In Table 2, we report arc elasticities by age groups comparing average medical spending for each of these scenarios. We obtain estimates, which suggest an inelastic demand for medical expenditures. The estimates range between -0.23 to -0.40 prior to age 50 and from -0.42 to -0.62 after that age. Despite very different methods, these estimates are remarkably close to those obtained from the RAND Health Insurance Experiment, which are approximately -0.2 to -0.3 depending on the type of care (Manning et al., 1987).

In a similar exercise to gauge how medical spending reacts to changes in income, we increase (and reduce) potential earnings by 25% relative to the baseline scenario. As Table 3 shows, the income elasticities range from slightly negative at younger ages to levels above 0.5 after age 50. These elasticities are close to micro estimates of the income elasticity of health spending (0.2-0.4) (Gerdtham and Jonsson, 2000). Hall and Jones (2007) obtain much higher elasticities (higher than 2) as they require a high elasticity to explain the rise in the fraction of income devoted to health as a result of income growth.

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 exercice.

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.[18]

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, Glei and Wilmoth, 2011). The former increased until the mid 1980s while the latter declined over the period. Estimates of mortality from smoking range from 10% of all deaths in 1965 to 24% of all deaths in 1985 (those would not have happened were it not for smoking). Preston, Glei 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

[18] Medical 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.

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.

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, $\delta_{2,j}^{1965} = e^{-\kappa_1 40}\delta_{2,j}$. Of course, this is a coarse modelling of improvements in productivity. For example, improvements may have resulted in expansion of treatments to untreated groups or disease-specific. Yet, given the summary measure of health we use, this provides a good approximation to overall improvements in medical technology. We define the annual rate of growth of mortality due to "other factors" as κ_2. Hence, we rewrite, $P_{d_{h,t}}^{1965} = e^{-\kappa_2 40} P_{d_{h,t}}$.[19] 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 the 1965 production function directly. 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 $\widetilde{m}_{1965}(\kappa_1, \kappa_2)$. Similarly, simulated life expectancy is given by $\widetilde{e}_{1965}(\kappa_1, \kappa_2)$. We use the percentage change in medical spending and life expectancy over that period, using life tables and National Health Account data to deflate our 2005 simulated average medical spending

[19] Two additional assumptions are made for trends in technology and other factors. First, we assume constant exponential growth for both trends. Improvements in life expectancy have been steady over this entire period. If both drive the increase in life expectancy, growth is likely to be steady over time. Of course, medical technology has improved in different domains over time. For example, progress treating heart attacks was achieved in the second part of the observation period (Skinner and Staiger, 2016). The second important assumption is that of rational expectations. Agents in the model take these trends into account when making decisions. Given steady progress in life expectancy, we think it is reasonable to assume that agents expect life expectancy for their cohort to be larger than period life expectancy. We are not aware of research that has examined whether agents correctly perceive improvements (changes) in life expectancy.

and life expectancy. Hence, we obtain the targets $m_{1965} = 470$ and $e_{1965} = 67.1$. 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 $\widehat{\kappa}_1 = 0.0172$ and $\widehat{\kappa}_2 = 0.003$.

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 observe 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 4, we report the results of the simulations in terms of total medical expenditures, out-of-pocket medical expenditures and life expectancy at age 25 and age 50. We also report a welfare measure based on the comparison of average expected lifetime 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 \$681.7 from \$487.1 at baseline. We estimate that life expectancy increases very little due to income growth alone. 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 37% of average consumption expenditures in the 2005 environment.

Improvements in insurance from the 1965 baseline do not increase medical expenditures by a large amount. With 2005 insurance parameters, average medical expenditures increase to \$700.1. Longevity increases by 0.2 years due to the expansion of insurance. The welfare gains from the expansion of insurance are modest. They represent 2% 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 \$487.1 to \$1877.8. The increase in longevity at age 25 is large: 7.9 years. Welfare gains, as a result of technological change represent 47% of annual consumption in the 2005 environment. We can compare this result to estimates of the value of life. Aldy and Viscusi (2004) suggest that \$200,000 is a reasonable estimate for the value of a life year. This suggests that the additional 7.9 years are worth roughly \$1.58 million. Lifetime consumption (without discounting) is \$2.66 million in the 2005 environment. Using the compensating variation estimate of 47%, we obtain a willingness to pay of \$1.25 million, consistent in order of magnitude with the rule-of-thumb estimate.

The negative mortality effect of other factors on longevity in 1965 is large (2 years). However, an interesting comparison is the one between the technology scenario and the 2005 scenario which imposes all trends (income, insurance, technology and other trends, including complementarity). Longevity is 0.9 years lower in this scenario, compared to the technology only scenario. This is remarkably similar to the estimate of Preston, Glei and Wilmoth (2011) who report that male life expectancy would be 0.9 years higher without the trend in smoking alone.

These separate individual contributions leave 59% for complementarity effects in medical expenditures 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 different story emerges for 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, but were substantially outweighed by improvements in technology.

To understand how these complementarity effects lead to higher spending, we run scenarios that combine some of these changes. First, we consider changes to insurance and to technology to occur jointly. This accounts for 45.6% of the total change in medical expenditures compared to 36.3% if we add the separate contributions of each factor. Hence, there is some complementarity between insurance and technological change. We then do the same with changes to income. When we implement both productivity growth and income growth, we can explain 77.9% of the increase in total spending. We can compare this to the sum of each change, 35.9%. Finally, we consider both changes to income and insurance keeping technology constant to 1965 level. This yields only a slight complementarity effect. Hence, most of the complementarity effect appears to come from the complementarity between income and technology.

Overall, the welfare gains from higher health-care spending appear substantial. The estimates suggest that the benefits in terms of better health and longevity, valued at $1.58 million, far outweigh the costs in terms of higher health spending, about $4,400 per year, or $330,000 over the lifetime of someone living to age 75. The rise of longevity is mostly the result of improvements in the productivity of health care while the rise in health spending would have been more modest if incomes had risen more slowly.

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 are consistent with evidence from the literature. The estimated model enables counterfactual exercises to reconstruct the changes experienced over the period 1965 to 2005.

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 1.7% per year, along with an independent adverse effect on mortality rates from smoking and obesity at a rate of 0.3% per year, could rationalize the growth observed in income and health insurance generosity over the period.

Starting from 1965, we estimated that trends in income growth, the generosity of health insurance, technology and other factors (e.g., trends in smoking and obesity) independently could not explain the observed growth in health-care spending. But, when introduced together, their mutual reinforcement led to rapid growth in spending. Put simply, growth in income and insurance is not worth much without access to a more productive health-production technology. According to our estimates, such complementarity effects accounted for more than half of the increase observed in medical expenditures over the period. For longevity, 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 67% of 2005 consumption expenditures. Similar to health-care spending, complementarity effects are also important for explaining the growth in longevity, with an estimated one third coming from that source.

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 when technological progress is potentially growing at the same pace across countries. Complementarity between factors may exacerbate small differences. The U.S. has had both large income growth and a large expansion of health insurance coverage. Even if technological progress 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 low 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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A Condition for Complementarity in Stylized Model

Using the utility function as in Hall and Jones (2007), and a simple functional semi-log specification for the production function

$$
\begin{aligned}
u(c) &= b + \frac{c^{1-\sigma}}{1-\sigma} && (12) \\
L(z,m) &= L_{min} + z\log(m), && (13)
\end{aligned}
$$

the first-order condition becomes

$$
bc^{\sigma} + \frac{c}{1-\sigma} = \frac{m}{z}\left[L_{min} + z\log(m)\right]. \qquad (14)
$$

Differentiate (14) w.r.t. y (and note that $c = y - m$) to obtain

$$
\left[\frac{L_{min}}{z} + \log(m) + 1 + \sigma bc^{\sigma-1} + \frac{1}{1-\sigma}\right]\frac{\partial m}{\partial y} = \sigma bc^{\sigma-1} + \frac{1}{1-\sigma}. \qquad (15)
$$

For the calibrated parameters and values for investment m, income y and consumption c of section 2, we have $u(c) > 0$ for both 1965 and 2005 values and hence $bc^{\sigma-1} + 1/(1-\sigma) > 0$ and $\sigma bc^{\sigma-1} + 1/(1-\sigma) > 0$ (since $\sigma = 1.424 > 1$). Thus $\partial m/\partial y > 0$.

Likewise, differentiating (14) w.r.t. z we obtain

$$
\left[\frac{L_{min}}{z} + \log(m) + 1 + \sigma bc^{\sigma-1} + \frac{1}{1-\sigma}\right]\frac{\partial m}{\partial z} = \frac{m\,L_{min}}{z^2}. \qquad (16)
$$

Thus $\partial m/\partial z > 0$.

To better understand interactions between income y and technology z, differentiate (15) w.r.t. z (or alternatively, differentiate (16) w.r.t. y) to obtain:

$$
\begin{aligned}
\left[\frac{L_{min}}{z} + \log(m) + 1 + \sigma bc^{\sigma-1} + \frac{1}{1-\sigma}\right]\frac{\partial m^2}{\partial y \partial z} &= -\sigma(\sigma-1)bc^{\sigma-2}\frac{\partial m}{\partial z} + \frac{L_{min}}{z^2}\frac{\partial m}{\partial y} \\
&+ \left[\sigma(\sigma-1)bc^{\sigma-2} - \frac{1}{m}\right]\frac{\partial m}{\partial z}\frac{\partial m}{\partial y}. \qquad (17)
\end{aligned}
$$

Complementarity of income y and technology z in health spending m requires $\partial m^2/\partial y \partial z > 0$ and hence

$$-\sigma(\sigma-1)bc^{\sigma-2}\frac{\partial m}{\partial z}+\frac{L_{min}}{z^2}\frac{\partial m}{\partial y}+\left[\sigma(\sigma-1)bc^{\sigma-2}-\frac{1}{m}\right]\frac{\partial m}{\partial z}\frac{\partial m}{\partial y}>0. \tag{18}$$

Substituting expressions (15) and (16) into (18) we obtain

$$\left[\frac{L_{min}}{z}+\log(m)+1+\sigma bc^{\sigma-1}+\frac{1}{1-\sigma}\right]\left\{-\sigma(\sigma-1)bc^{\sigma-2}m+\left(\sigma bc^{\sigma-1}+\frac{1}{1-\sigma}\right)\right\}$$
$$+\left[\sigma(\sigma-1)bc^{\sigma-2}m-1\right]\left(\sigma bc^{\sigma-1}+\frac{1}{1-\sigma}\right)>0.$$

Further simplifying this expression we obtain the condition

$$\left[\frac{L_{min}}{z}+\log(m)\right]\left\{-\sigma(\sigma-1)bc^{\sigma-2}m+\left(\sigma bc^{\sigma-1}+\frac{1}{1-\sigma}\right)\right\}$$
$$+\left(\sigma bc^{\sigma-1}+\frac{1}{1-\sigma}\right)^2-\sigma(\sigma-1)bc^{\sigma-2}m>0, \tag{19}$$

It is somewhat tedious but straightforward to show that for the calibrated parameters and values for investment m, income y and consumption c, condition (19) holds for both 1965 and 2005. Thus $\partial m^2/\partial y \partial z > 0$.

B 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 occurence 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 by $\zeta(t)$. 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

We use the Welfare Benefit Database (`http://www.econ2.jhu.edu/people/moffitt/datasets.html`) constructed by Robert Moffitt. We transform amounts into 2005 dollars using the CPI. We use the average over the period 1965 to 2005, 13,735$. Figure B.1 shows the evolution of the resource floor over this period.

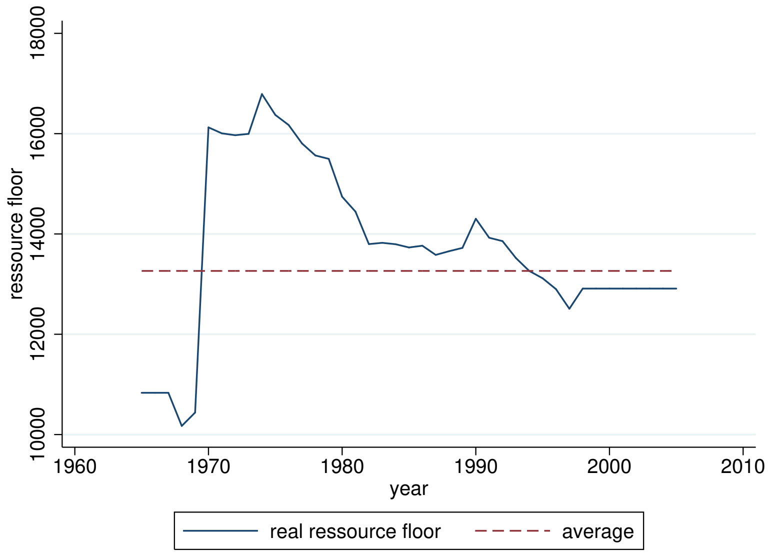


Figure B.1: Resource Floor 1965-2005 (2005 dollars): Estimates from the Welfare Benefits Database (Moffitt, 2002).

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, 0.083 for those on Medicaid, 0.256 for those with employer plans and 0.215 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	0.425	1.000	1.000	0.734
Medicaid	0.013	0.083	0.335	0.228
Private	0.111	0.256	0.510	0.348
Medicare	0.069	0.215	0.484	0.312

C Data Sources

Panel Study of Income Dynamics

We use the PSID version created by the Cornell Equivalent File Project (CNEF).[20] 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 25 to 84. Some of the analysis further restricts the sample. Sample weights are used whenever possible in order to make the sample representative of this population. 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 57,261 observations are available across all years. 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.

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.

[20] The files can be obtained at the CNEF homepage

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).

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.

Table C.1 provides descriptive statistics on the master sample from PSID.

	obs.	Mean	Std. Dev	Min	Max
Age	57,261	45.48103	14.47063	25	84
Education (college)	54,630	.50108	.5000034	0	1
Work	57,261	.8397339	.3668559	0	1
Earnings	56,469	42272.73	37077.41	0	249951.1
Other Income	56,937	17521.27	23027.49	0	248947.3
Wealth	24,196	208155.1	308670.5	0	1999702
Health	obs.	Percentage			
Poor-fair	7,007	12.24			
Good	14,334	25.03			
Excellent	35,920	62.73			
Birth Year	obs.	Percentage			
1925 and less	5,783	10.10			
1926-1934	6,059	10.58			
1935-1944	7,755	13.54			
1945-1954	16,773	29.29			
1955-1964	14,481	25.29			
1966 and more	6,410	11.19			

Table C.1: Descriptive Statistics for PSID 1984 - 2005

Medical Expenditure Panel Study

We use data from years 1996 to 2008 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 84 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. Our main analysis file contains 54,159 person-year. For the estimation of the health-production function, the sample is reduced to 14,202 respondents in large part because information on smoking comes from the NHIS sample adult files merged with MEPS.

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 2011. Hence, we link the MEPS record to the mortality follow-up conducted in NHIS. We then define mortality as occuring 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. Figure C.1 shows the close correspondence although the small sample size beyond age 75 yields more volatile mortality rates.

Figure C.1: Comparison of Mortality Rates with MEPS: Period mx and Cohort mx refer to life table estimates from the Social Security Administration. Estimates from the MEPS-NHIS matched mortality follow-up study.

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 1996 to 2008, excluding long-term care (LTC) expenditures since MEPS surveys the non-institutionalized population. Finally we cap medical expenditures at $100,000 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 a control for estimating the health-production function. Information on smoking is not available in MEPS. Since each MEPS panel is randomly drawn from the National Health Interview Survey of the previous year, we use NHIS information on smoking. However, not all NHIS respondents answer those questions. Only one sample adult per household is given the questionnaire on smoking. Hence, from a total sample of 54,159 in MEPS, we have 19709 respondents with valid information on smoking.

Table C.2 provides descriptive statistics on the sample.

	obs.	Mean	Std. Dev	Min	Max
Age	54,159	47.88698	14.76017	25	84
Household Income	54,157	34569.06	31495.72	0	426266
Obesity (BMI>30)	39,230	.2808565	.4494233	0	1
Ever Smoke	19,709	.5372672	.4986219	0	1
Mortality rate	39,403	.0108586	.0172435	.0012	.12114
Med. Exp.	53,835	4747.627	10700	0	99724.8
Insurance Coverage	obs.	Percentage			
Private	37,551	69.33			
Public	7,179	13.26			
Uninsured	9,429	17.41			
Health	obs.	Percentage			
Poor-fair	7,795	14.48			
Good	15,684	29.13			
Excellent	30,360	56.39			

Table C.2: Descriptive Statistics MEPS 1996- 2008

D Auxiliary Processes and Initial Conditions

Earnings

We select PSID men aged 25 to 65 working full-time prior to 1997 (2-year gap between waves after 1997). The estimation sample is an unbalanced panel consisting of 4,100 workers. The specification for annual real gross earnings of the household head is given by

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

where the earnings shocks for the individual i $\eta_{it} = \log y^e_{it} - E[\log y^e_{it}|\pi_{i0}, t]$ follows an AR(1) process $\eta_{it} = \rho\eta_{it-1} + \varepsilon_{it}$, $\varepsilon_{it} \sim N(0, \sigma^2_\varepsilon)$. 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 48 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 $\widehat{\rho} = 0.953$ and $\widehat{\sigma}^2_\varepsilon = 0.024$. Hence, earnings shocks are quite persistent. Figure D.1 reports the average earnings profile along with plus or minus 2 standard deviations using the unconditional variance of η_{it}.

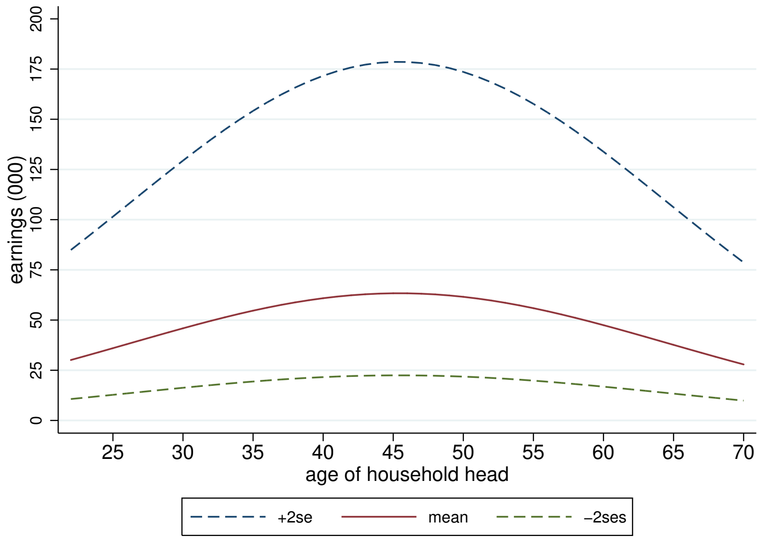


Figure D.1: Earnings predictions from PSID: Predicted mean along with +- 2 standard deviation based on unconditional variance of permanent shock.

We have tested whether health was predictive of earnings conditional on age with the fixed effect regresion. We could not reject the null hypothesis that health was not predictive of earnings (results available upon request).

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. Table D.1 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 in Figure D.2.

Parameters	Estimates	Std. Error
π_3	-24887.7**	1726.7
π_5	1012.6**	73.5
π_6	-8.668**	0.739
π_4	0.325**	0.010
Obs.	53508	

Table D.1: Estimates of Other Income Process from PSID.

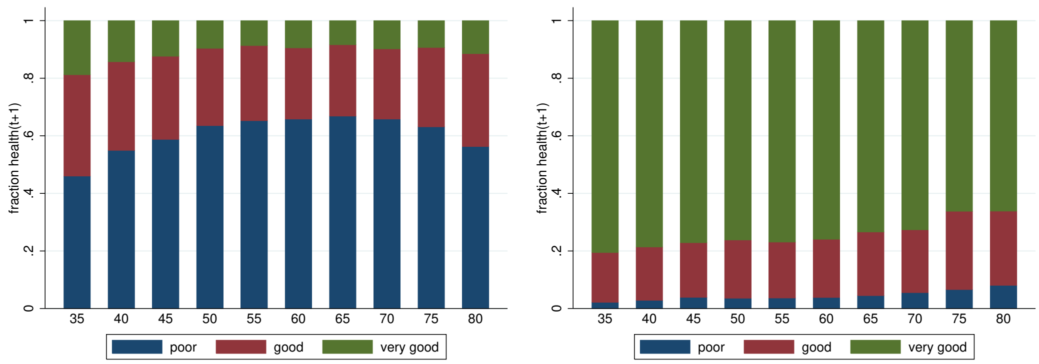
Figure D.2: Other Income from PSID: Spouse earnings and Social Security benefits. Predicted mean along with 5th and 95th percentile generated from variation in respondent's earnings.

Initial Distribution of State Variables

We select male household heads aged 25 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 20.8% of respondents do not have employer provided insurance, 39.2% have employer-tied coverage and 40.0% 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. We sample with replacement to obtain an initial population of 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.

E Estimation of Health Processes

We use MEPS to estimate health and mortality processes. We use data on males aged 25 to 85. In Figure E.1, we report one year transition rates from health states at (t) to health states at (t+1) from all waves of MEPS.



(a) From Poor Health (t) (b) From Very Good Health (t)

Figure E.1: **MEPS One-Year Transition Rates Across Health States**

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 endogeneous. 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} (Petrin 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 Table E.1. 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)	1.604**	0.185
φ_2 (good)	-0.992**	0.077
φ_3 (>good)	-1.435**	0.074
φ_6 (log income)	0.151**	0.014
$\varphi_{7,1}$ (obese)	0.372**	0.056
$\varphi_{7,2}$ (smoking)	-0.146**	0.052
φ_8 (age)	0.083**	0.001
N	14308	
R-squared	0.184	
Partial-F log income	106.22	

Table E.1: First-step Estimate of Production Function: OLS coefficients along with standard errors. ** denotes $p < 0.05$.

We compute residuals $\widehat{\nu}_{it}$, which we plug into the health process:

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

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 Table E.2. 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)	-1.220**	0.309	-3.187**	0.4211
δ_0 (good)	2.487**	0.115	3.476**	0.186
δ_0 (>good)	3.037**	0.148	5.964**	0.225
δ_1 (age)	-0.046**	0.008	-0.096**	0.011
δ_2 ($\log m_{it}$)	0.610**	0.101	1.267**	0.132
δ_3 ($\log m_{it}^2$)	-0.021**	0.003	-0.038**	0.003
$\delta_{4,1}$ (obese)	-0.343**	0.089	-0.773**	0.106
$\delta_{4,2}$ (smoking)	-0.223**	0.067	-0.346**	0.087
δ_5 ($\widehat{\nu}_{it}$)	-0.523**	0.092	-1.067**	0.126
N	14202			

Table E.2: Estimates of Production Function: multinomial logit coefficients along with bootstrap standard errors. ** denotes $p < 0.05$.

The parameter estimates of δ_{5j} are jointly significantly different from zero which reveals that m_{it} is endogeneous. 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

Table E.3.

Parameters	Estimate	Std. Error
$\delta_{7,1}$ (constant)	-7.712**	0.244
$\delta_{7,2}$ (good)	-1.356**	0.108
$\delta_{7,3}$ (>good)	-1.873**	0.117
δ_6 (age)	0.074**	0.003
N	45885	

Table E.3: Mortality Process Estimates with Standard Errors.

There is one issue with the estimated mortality process. 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 mortality process are equal to the Social Security mortality rates.

F Solution Method and Estimation of Preference Parameters

Solution Method

Starting at the last age, which we set at $T = 120$, 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 use golden section search. We first condition on a choice of consumption and then find optimal $m^*(c)$ conditional on that choice of consumption. We then do golden-section search on c using $m^*(c)$. 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. The solution method produces reasonable decision rules.

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 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. Next, the average medical expenditures by age are computed from MEPS. We follow the same strategy. We then predict average medical expenditures for someone born between

1935 and 1945.

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. For each respondent in MEPS and PSID, we complement mortality data from PSID and MEPS by imputing mortality so as to match SSA mortality rates.

Estimator

Denote by N the total sample size of PSID and MEPS. As in French (2005), we treat the combined PSID and MEPS dataset using a missing data analogy. The total sample is that of PSID and MEPS but respondents only respond to one of the surveys and contribute to moments unequally depending on age, etc. We assume that this missing data problem is random and therefore can construct the jth moment condition involving the variable z using

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

where $z_{i,j}(\theta_0)$ is the adjusted data of respondent i contributing to the moment condition (there are n_j such respondents), and finally $\widetilde{z}_{s,j}(\theta)$ 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 $\widetilde{g}_N(\theta)$ which has expectation zero at $\theta = \theta_0$. The Method of Simulated Moment (MSM) estimator is given by

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

where W_N is the inverse of the covariance matrix of the adjusted data and $\tau = N/S$. Given some regularity conditions, the MSM estimator is consistient 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

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

where G_N is the matrix of derivatives of the moment vector with respect to the parameters.

Since the objective function is generally not smooth and has local minima, we use the Nelder-Mead algorithm to find the minimum. We tried various starting values until we found a global minimum.

Figures

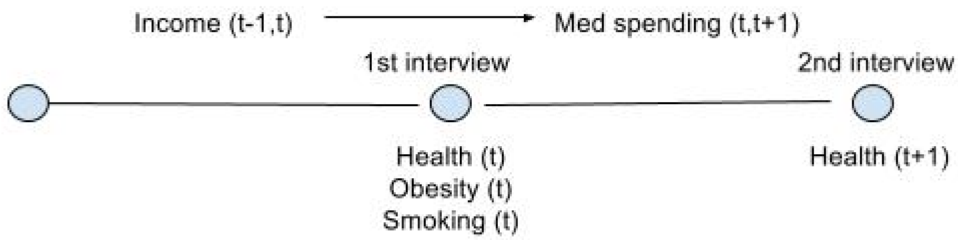


Figure 1: **Timing of the Variables for the Estimation of the Production Function in MEPS.**

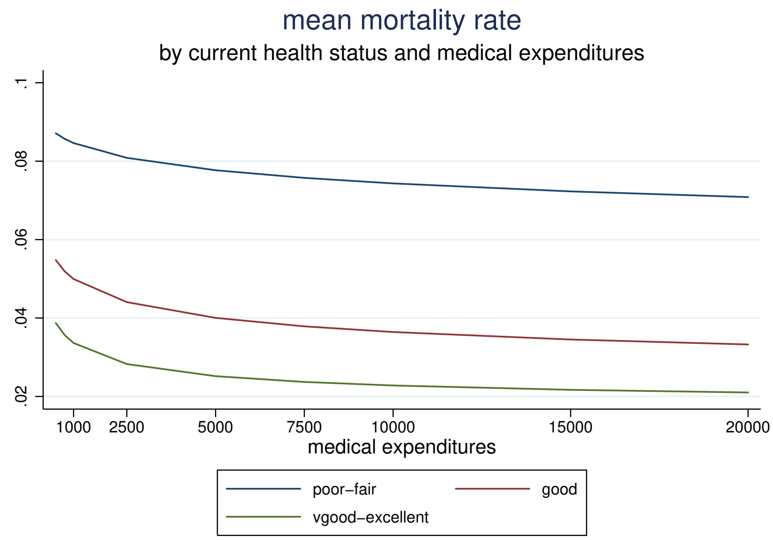


Figure 2: **Mortality Rates by Current Health Status and Level of Medical Expenditures, Age 65+**: Effects are obtained by combining the marginal effects from the health process weighted by the conditional mortality probabilities by health status and averaged over the population age 65+.

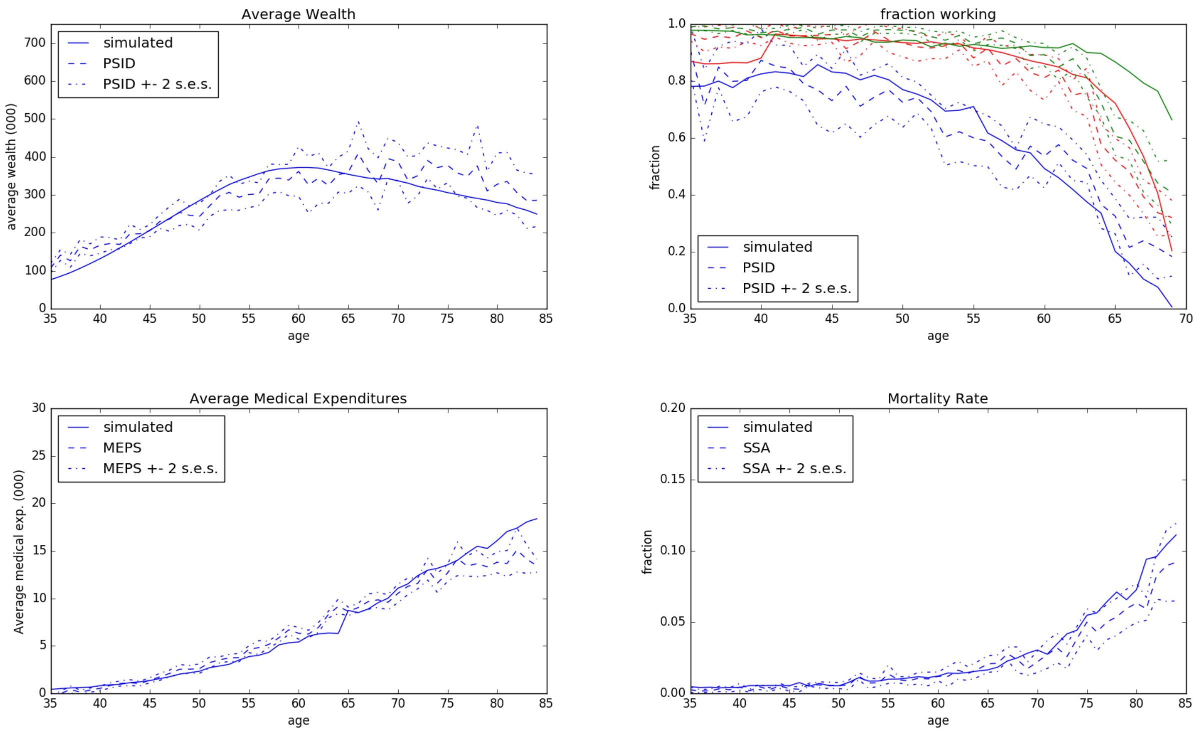


Figure 3: **Age Profiles from Data and Simulations:** The solid lines show the average profile from the simulation. The dashed lines show the profiles from Data; PSID for wealth and work, MEPS for medical expenditures and SSA life tables for mortality. For the top-right figure, the fraction working is shown by health status (poor health is shown in blue, good health in red and very good health in green).

Tables

Parameter	Estimates
σ	3.3824
	(0.5795)
γ	0.6507
	(0.0152)
ϕ_2	0.4803
	(0.0603)
ϕ_1	0.7826
	(0.0259)
β	0.9598
	(0.0054)
α_1	-0.1705
	(0.1117)
α_2	0.7625
	(0.1801)
α_3	-0.4003
	(0.1659)
ξ	1.1067
	(0.6119)
Criterion	172.780
D.F.	246

Table 1: **Preference Parameter Estimates by Method of Simulated Moments**: Standard errors computed at the solution using the formula shown in Appendix E. The overidentifcation test value is given by the value of the criterion function of the MSM estimator at the minimum and is distributed as a chi-square with degrees of freedom equal to the number of moments minus the number of parameters to estimate.

Age	$\overline{m}(95)$	$\overline{m}(75)$	$\overline{m}(50)$	$\overline{m}(25)$	$\epsilon_p(95)$	$\epsilon_p(75)$	$\epsilon_p(50)$
30-34	234.3	247.8	273.9	319.8	-0.238	-0.25	-0.232
35-39	422.9	452.5	500.6	588.3	-0.287	-0.252	-0.242
40-44	736.3	796.8	906.4	1097.8	-0.335	-0.322	-0.286
45-49	1255.6	1377.0	1594.9	2037.1	-0.392	-0.367	-0.365
50-54	1975.8	2194.8	2603.3	3457.3	-0.446	-0.426	-0.423
55-59	3003.6	3380.7	4102.8	5604.3	-0.502	-0.483	-0.464
60-64	4230.1	4766.1	5789.9	7642.8	-0.506	-0.485	-0.414
65-69	5132.5	5773.7	6970.7	9019.1	-0.5	-0.47	-0.384
70-74	6993.1	7863.9	9443.6	12066.3	-0.498	-0.456	-0.366
75-79	8098.6	9203.6	11143.5	14549.6	-0.543	-0.477	-0.398
80-84	8854.4	10245.0	12698.7	17274.2	-0.619	-0.535	-0.458

Table 2: **Co-insurance Elasticities of Health-Care Spending with Different Co-insurance scenarios**: The first four columns report average total medical spending by age group, $\overline{m}(\psi)$ for four levels of co-insurance ψ =(95%,75%,50%,25%). These rates apply to all forms of coverage (Employer provided, individual, Medicare and Medicaid). The last three columns report arc elasticities, $\epsilon_p(\psi)$ for changes from 95% to 75%, from 75% to 50% and from 50% to 25%.

Age	$\overline{m}(-50)$	$\overline{m}(ref)$	$\overline{m}(+50)$	$\epsilon_y(-50)$	$\epsilon_y(+50)$
30-34	332.1	309.8	305.2	-0.366	-0.125
35-39	568.9	553.7	560.1	-0.101	0.061
40-44	958.9	1001.1	1051.3	0.125	0.213
45-49	1577.7	1772.3	1996.2	0.29	0.443
50-54	2356.4	2890.5	3512.4	0.455	0.63
55-59	3437.7	4517.3	5844.5	0.555	0.726
60-64	4494.8	6071.5	7913.6	0.562	0.653
65-69	7209.8	9127.2	11047.6	0.645	0.556

Table 3: **Earnings Elasticities of Health-Care Spending with Different Levels of Earnings**: The first four columns report average total medical spending by age group, $\overline{m}(x)$ for 3 levels of earnings x =(Baseline - 50%, Baseline, Baseline + 50%). The last two columns report arc elasticities, $\epsilon_y(x)$ for a 50% change from each point.

Outcome		$\overline{m}$	$\overline{oop}$	e_{25}	e_{50}	CV(%)
1965		487.1	356.0	42.3	22.5	
Income		681.7	480.3	42.5	22.7	0.37
	$\Delta\%$ Total	0.044	0.127	0.034	0.027	
Insurance		700.1	248.3	42.5	22.7	0.02
	$\Delta\%$ Total	0.048	-0.11	0.034	0.027	
Technology		1877.8	942.7	50.2	28.3	0.47
	$\Delta\%$ Total	0.315	0.6	1.127	1.076	
Other		501.7	368.3	40.3	21.0	0.04
	$\Delta\%$ Total	0.003	0.013	-0.279	-0.273	
Insurance+Technology		2499.0	729.5	50.4	28.6	0.48
	$\Delta\%$ Total	0.456	0.382	1.162	1.118	
Income+Technology		3928.9	1764.5	51.0	29.3	0.65
	$\Delta\%$ Total	0.779	1.44	1.249	1.258	
Income+Insurance		902.0	319.9	42.5	22.7	0.38
	$\Delta\%$ Total	0.094	-0.037	0.036	0.026	
2005		4902.8	1333.8	49.3	27.9	0.67

Table 4: **Simulation Scenario Results 1965-2005**: Average medical spending ($\overline{m}$), average out-of-pocket medical spending ($\overline{oop}$) and remaining life expectancy at age $x = (25, 50)$ (e_x) is reported for each scenario. The last column 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). Results in the first row pertain to the 1965 environment. The second row implements the 2005 income scenario keeping insurance and technology at their 1965 level. The third row implements the 2005 insurance scenario keeping 1965 income and technology constant. The fourth row implements the 2005 technology scenario keeping income and insurance at their 1965 level. The fifth row implements the change in mortality due to other factors. The sixth to eight row implement two changes simultaneously for growth in productivity, insurance and income. Finally, the last row reports results for the baseline scenario in 2005. Below each row we also report the fraction of the total change from 1965 to 2005 explained by each factor.