The welfare effects of nonlinear health dynamics: External appendix

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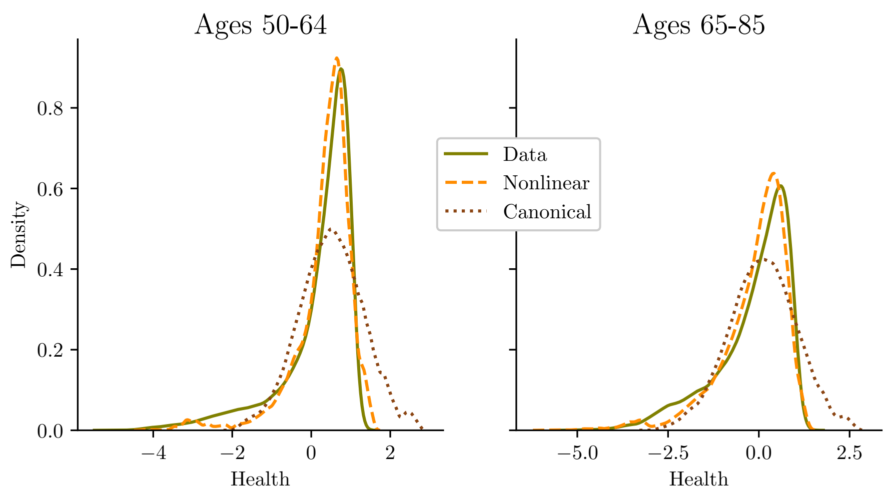
B Data

Table B.1: Descriptive statistics by age

	50-59	60-69	70-90
% working	79.5	40.7	6.8
annual hours worked	1926	1597	950
wages (£)	16775	12057	3576
wealth (1000 £)	128	169	193

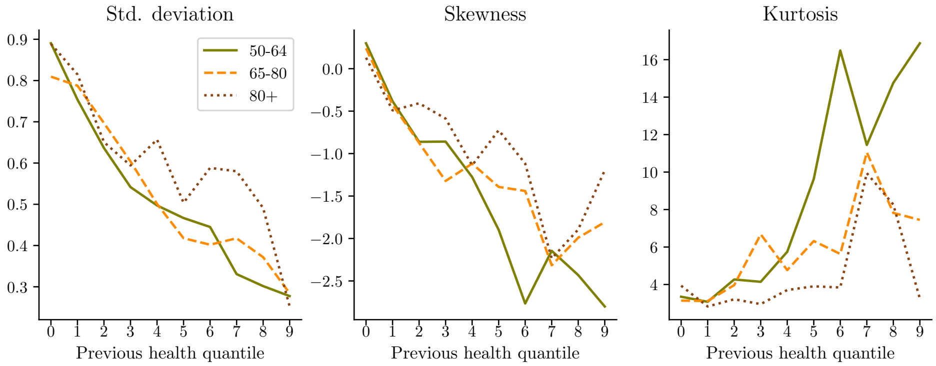
Note: ELSA data, waves 1-7. Annual hours worked are conditional on working, and are computed by multiplying average weekly hours by 46 working weeks. Annual earnings are similarly obtained from weekly earnings assuming continuous employment during the year. Wealth refers to total wealth, including housing but excluding pension wealth and is corrected for cohort effects (reference cohort 1946-1955 – see details in Appendix E).

Figure B.1: Health distributions by age



Note: Kernel density estimates of the distribution of health index (Data), and simulated data from the nonlinear and canonical models.

Figure B.2: Moments of health shocks by age and previous health deciles



Note: Higher moments conditional on previous period health from data. Health shock is defined as $\Delta h_t = h_t - h_{t-2}$.

C Health processes

C.1 Nonlinear health process

Following De Nardi et al. (2020), after estimating the health process using Arellano, Blundell and Bonhomme's procedure, we simulate many health histories and discretize the persistent and transitory components of health at each age in N dimensional grids. We then compute the transition matrices from t to $t+2$ for the persistent component (recall that our health data is biennial).[1]

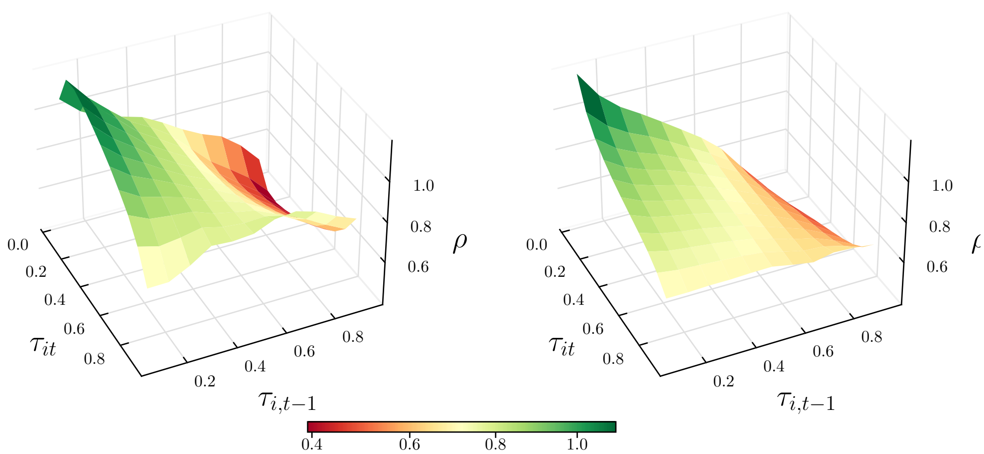
To reconcile this biennial health process with the annual time span in the life-cycle model, we assume that health remains constant in the period we do not observe, such that the transition matrix is the identity matrix from t_o to t_{o+1}, o being an odd number, and the matrix computed in the simulated data from t_{o+1} to t_{o+2}.[2]

Selection into mortality in the original data and the discretization of the process lead to underestimation of health in simulated health trajectories, after death probabilities conditional on health are applied to the process. Therefore, we apply an iterative procedure and rescale the original data at each age so that median simulated health conditional on survival coincides with median health in the data.

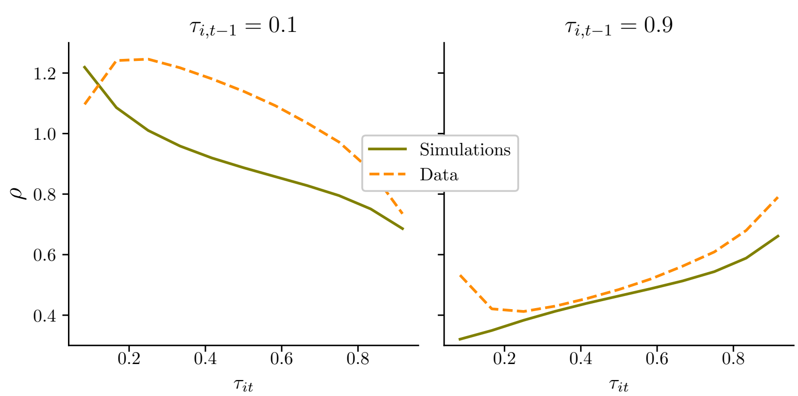
[1]Because of inconsistencies in the measurements of BMI from wave 7 onwards, the health measure and health dynamics are estimated using the first six waves only. We also estimate the death probabilities using six waves as ELSA data are linked to national death registers up to wave 6.

[2]We experimented with splitting the transition by computing the matrix T_1 satisfying $T_2 = T_1 \times T_1$, where T_2 is the matrix resulting from our simulations. The procedure is computationally intensive and does not always produce a real-valued solution.

Figure C.3: Estimates of the health processes



(a) Average persistence, nonlinear model vs data



(b) Average persistence by decile of initial health, nonlinear model

Note: Panel (a) reports estimates of (4) computed directly from data, and from simulations of the nonlinear model. Panel (b) displays sections of figures in Panel(a) C.3(a) taken at the 1st and 9th deciles of τ_{init}.

C.2 Canonical health process

To estimate the canonical health process, we first obtain health residuals by regressing the health index on a set of demographics, which includes a third-order polynomial in age, year of birth, education, and an indicator for having a partner.

We assume that health residuals are the sum of a persistent and a transitory component, as in (2). The persistent component follows an AR(1) process, $\eta_t = \rho\eta_{t-1} + \nu_t^H$, with $\nu_t^H \sim N(0, \sigma_\nu^2)$. The transitory component ϵ_t is an iid shock $\sim N(0, \sigma_\epsilon^2)$.

Table C.2: Canonical health process parameter estimates

Random component		
ρ	0.953	(0.016)
σ_ν^2	0.084	(0.023)
σ_ϵ^2	0.137	(0.028)
σ_0^2	0.450	(0.051)

The three parameters of the random component of the health process (σ_ϵ^2, σ_ν^2 and ρ) plus the initial variance at age 50 (σ_0^2) are identified by the variances and covariances of the health residuals h_{it}. The initial period variance ($t = 0$), the following periods variances ($t = 1, \dots, T$) and the lag ℓ covariances are equal to

$$\begin{aligned} Var(h_{i0}) &= \sigma_0^2 + \sigma_\epsilon^2 \\ Var(h_{it}) &= \rho^{2t}\sigma_0^2 + \frac{1-\rho^{2t}}{1+\rho^2}\sigma_\nu^2 + \sigma_\epsilon^2 \\ E(h_{it}h_{it-\ell}) &= \rho^\ell \left(\rho^{2(t-\ell)}\sigma_0^2 + \frac{1-\rho^{2(t-\ell)}}{1+\rho^2}\sigma_\nu^2\right) \end{aligned}$$

Identification requires at least three periods of data. Note that, given the biennial nature of ELSA data we consider lags ℓ that are multiple of 2 up to lag 8. Table C.2 reports the estimates.

C.3 Mortality

To compute mortality rates we discretize health in four quantiles defined by the 20, 30, and 50th percentile cutoffs. We assume that mortality risks perceived by the individuals are consistent with the life tables, and rescale estimated mortality in each health-age group in order to match the life tables' mortality rates.

D Earnings process

The earnings process has a deterministic component, $\omega_e(h_t, t)$, which depends on health and age. The composite error term ψ_t is the sum of a persistent (ϑ_t) and a transitory (υ_t) component. Persistence in wages is captured by an AR(1) process ϑ_t.

$$\begin{aligned} \log e_t = \ & \omega_e(h, age_t) + \psi_t \qquad (1) \\ & \psi_t = \vartheta_t + \upsilon_t \\ & \vartheta_t = \rho_e \vartheta_{t-1} + \nu_t^e, \quad \nu_t^e \sim N(0, \sigma_{\nu^e}^2). \end{aligned}$$

We assume that at time $t-1$ the individual knows ϑ_{t-1}, but he only knows the distribution of the innovations ν_t^e. We further assume that υ_t captures measurement error only.

Table D.3: Earnings process parameter estimates

Random component		
ρ_e	0.896	(0.054)
$\sigma^2_{\nu^e}$	0.034	(0.021)
σ^2_{υ}	0.226	(0.031)
σ^2_0	0.148	(0.039)

Table D.3 reports the estimated parameters of the earnings process stochastic component. To identify the parameters we use the same moments used to estimate the canonical health process (see Appendix C).

E Wealth profile

Our measure of wealth includes both housing and non-housing wealth. Blundell et al. (2016) report real house prices in England from 2002 to 2013 and document a 40% increase between 2002 and 2004, the first two waves of ELSA. We assume that the house price increase and the resulting wealth increase for homeowners do not affect individual decisions in terms of consumption, retirement, and labor market participation. Therefore, we strip out house price changes by dividing net primary housing wealth by the house price index, using as reference year 2004, and we assume a price increase equal to the real rate of return on other financial assets. The corrected net primary housing wealth is added up to net non-housing wealth and used to estimate the wealth profile.

To correct for cohort effects, we regress wealth a_{it}, on an individual specific effect f_i, a polynomial in age and unemployment rate U_t, proxying for aggregate time effects.

$$a_{it} = f_i + \sum_{n=1}^{S} \pi_n age_{it}^n + \pi_U U_t + u_{it} \tag{2}$$

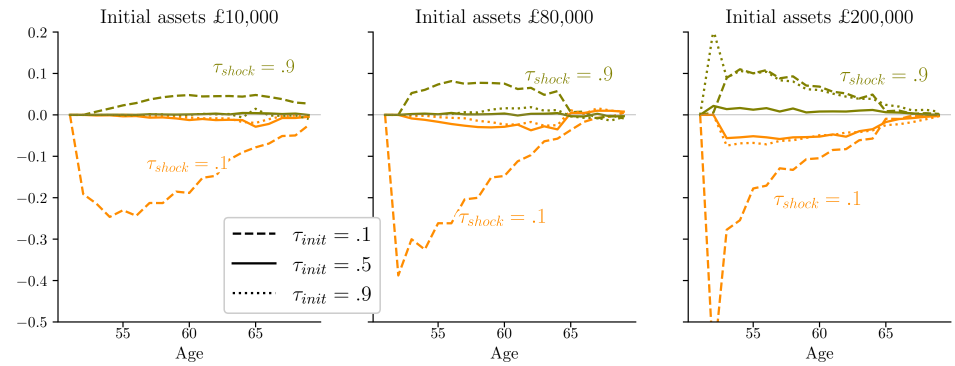
This specification allows the estimation of age parameters accounting for individual fixed effects and time effects.

The estimated fixed effects $\hat{f}_i$ are regressed on a set of ten-year cohort dummies, this allows to compute the conditional expectation of $\hat{f}_i$ for a specific cohort of individuals, $E[\hat{f}_i|cohort = c]$. We then simulate from the estimated model fixing unemployment rate at 4.9% and the individual fixed effect with the average fixed effect for the cohort of interest. Specifically, we replace f_i with $\tilde{f}_i = \hat{f}_i - E[\hat{f}_i|cohort_i] + E[\hat{f}_i|cohort = c]$. The reference cohort c includes individuals born between 1946 and 1955.

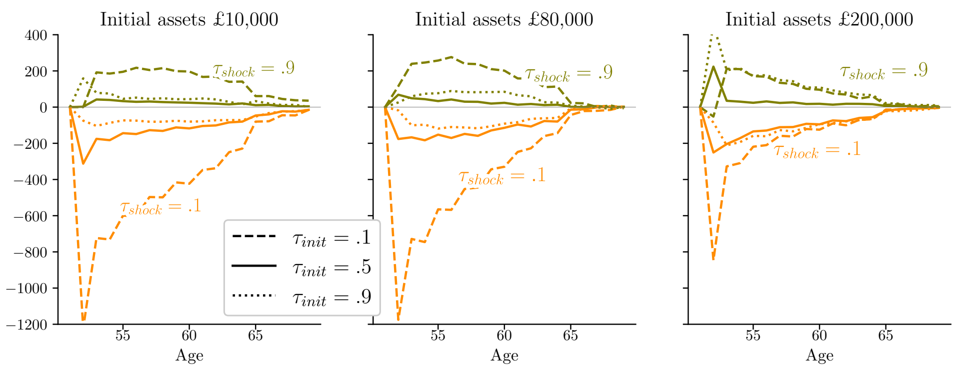
F Additional results

Figure F.4: Effects of health shocks, from different wealth levels

(a) Labor force participation



(b) Hours worked



Note: The figures illustrate, for different values of initial assets in the canonical model of health dynamics, the age profiles of the difference in labor force participation and hours worked between individuals subject to a permanent component of health shock τ_{shock} and individuals subject to $\tau_{shock} = 0.5$, starting from different initial levels of the permanent component (τ_{init}). Averages over 5,000 simulated histories of individuals starting at age 50 with the same level of assets indicated at the top of each panel.

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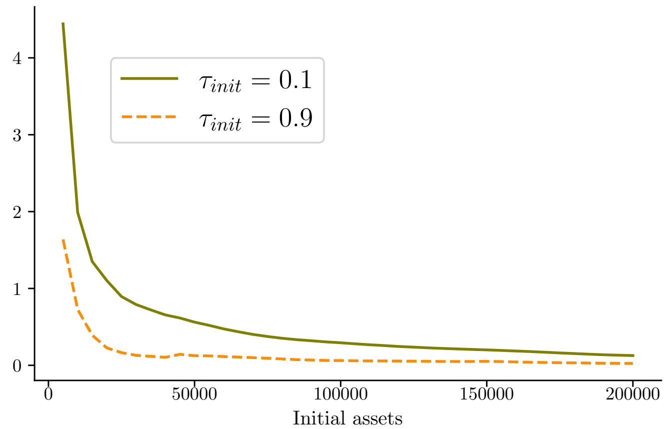
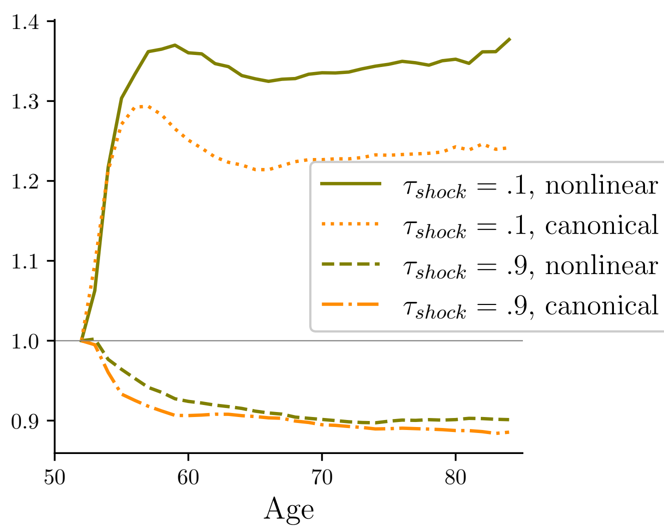
Figure F.5: Willingness to pay to avoid a bad shock (fraction of initial assets)



The figure reports the asset transfer, as a fraction of initial assets, that would make a person indifferent between being subject to $\tau_{shock} = .1$ at age 52, starting from different level of the permanent component of health τ_{init}, and receiving the transfer, or not being subject to the shock.

Figure F.6: Assets, coefficient of variation following good and bad shocks, relative to a median shock



The Figure plots the age profiles of the ratio of the coefficients of variations of accumulated assets for levels of $\tau_{shock} = \{0.1, 0.9\}$, and the coefficient of variation of the same variable for $\tau_{shock} = 0.5$. Individuals starting with $\tau_{init} = 0.1$ and initial assets equal to £10,000. Average of 15,000 histories per simulation.

Table F.4: The effect of health and its components

(a) Health: 25th percentile

Effects removed	Assets	Income	Empl.	Hours
All (relative to baseline)	-10.3%	-9.9%	-1.0%	-11.2%
Decomposition:				
Mortality	-0.9%	-0.2%	-0.3%	+0.1%
Time cost	-8.1	-7.5	+0.5	-11.1
Wages	-2.7	-3.3	-0.7	-0.8
Mortality+Time	-8.6	-7.6	+0.3	-10.9
Mortality+Wages	-3.5	-3.5	-0.9	-0.7
Time+Wages	-9.9	-9.9	-0.9	-11.4

(b) Health: 50th percentile

Effects removed	Assets	Income	Empl.	Hours
All (relative to baseline)	-2.6%	-1.9%	+4.2%	-5.8%
Decomposition:				
Mortality	+0.2%	-0.2%	-0.3%	+0.2%
Time cost	-2.9	-2.2	+3.3	-5.3
Wages	-0.6	-0.4	+1.3	-1.0
Mortality+Time	-3.2	-2.7	+3.0	-5.6
Mortality+Wages	-0.4	-0.5	+1.1	-0.8
Time+Wages	-2.6	-1.6	+4.3	-5.5

(c) Health: 90th percentile

Effects removed	Assets	Income	Empl.	Hours
All (relative to baseline)	+15.9%	+21.0%	+15.9%	+13.1%
Decomposition:				
Mortality	+1.4%	-0.1%	-0.1%	+0.4%
Time cost	+9.4	+14.7	+12.6	+13.6
Wages	+3.9	+5.6	+4.8	-1.5
Mortality+Time	+9.9	+13.3	+12.3	+13.0
Mortality+Wages	+5.5	+5.3	+4.8	-1.2
Time+Wages	+14.9	+22.5	+16.2	+13.6

Note: Each panel reports percent changes from the baseline after assigning everyone either the mortality rate, time cost of health, or wage offer computed at the percentile of the age-specific health distribution indicated. Assets and (disposable) Income in £1000 averaged throughout the life cycle. Employment rate averaged from age 50 to 69. Hours are annual, conditional on employment.

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