Heterogeneous and Uncertain Health Dynamics and Working Decisions of Older Adults

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Motivation

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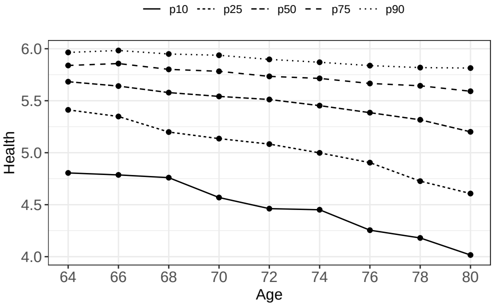
  - Changes in health affect retirement expectations of workers (McGarry, 2004)
- Mostly ignored: heterogeneity at which health deteriorates with age

Motivation

Heterogeneous health dynamics

Figure: Health percentiles with age from the Health and Retirement Study



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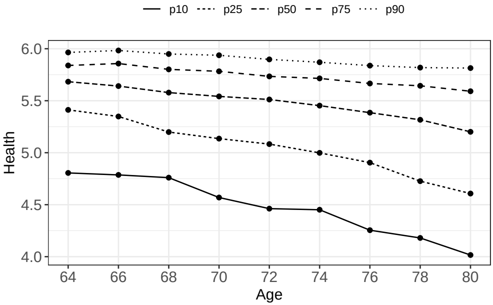

- In my model, I find some of this variation is individidual heterogeneity in health profiles

Motivation

Heterogeneous health dynamics

- Heterogeneity's effects on working decisions depend on what people know

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- Hence, role for an analysis of uncertainty about health profiles

Research question

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  1. To document this heterogeneity
  2. To measure individuals' information about their own health profile
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- Do health beliefs play a role in working decisions of older adults?

Empirical strategy

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  1. To document this heterogeneity
     - Dynamic model of health with heterogeneous changes rates with age
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  3. To study its effects on working decisions of older adults
     - Estimate working decision as a function of those beliefs using a Neural Network approach

Relation to the literature

Literature on health dynamics

- Contoyannis et al (2004), Halliday (2005), Hernandez-Quevedo et al (2008), Heiss (2011), Heiss et al (2014)

My contribution: heterogeneous profiles with age

Literature on micro/empirical learning

- Guvenen and Smith (2014), Currie and McLeod (2020), Arcidiacono et el (2016), Stinebricker and Stinebricker (2014), Delavande and Zafar (2019)

My contribution: combine expectations and outcome data, allow for systematic bias

Literature on outcomes of older individuals and effects of health

- Bound et al (1999), French (2005), Disney et al (2006), McGarry (2004), Maurer et al (2011)

My contribution: role of health beliefs

Data

- Health and Retirement Study (HRS)
  - Longitudinal data, collected every 2 years, running since 1992
  - Representative of individuals 50 years and older in the US
  - Includes measures of health, survival expectations, labor supply
- This analysis uses 9 waves, 1998-2014

Step 1: heterogeneous health dynamics

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  - Construct health h_{it} by Confirmatory Factor Analysis using 11 measures
  - Better health is characterized by larger values of h_{it} (fewer chronic conditions)

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$$h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it}, \quad t \text{ denotes age, } \epsilon_{it} \sim N$$

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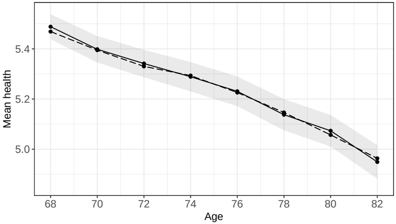
  - Random coefficient model estimated by MLE

measures integrated likelihood

Step 1: heterogeneous health dynamics

Results



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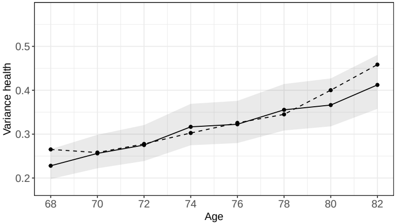

(b) Variance of h_{it}

- Slope heterogeneity helps explaining the increasing variance with age

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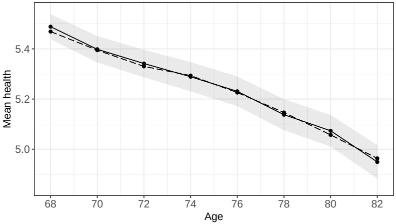

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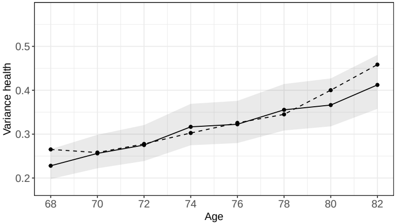

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  - Overestimating variance

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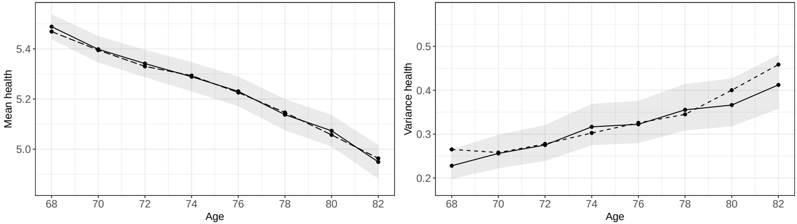

(a) Mean of h_{it} (b) Variance of h_{it}

- Slope heterogeneity helps explaining the increasing variance with age
- Ignoring survival equation leads to
  - Underestimating mean
  - Overestimating variance
- Results are robust to heteroskedastic errors and to using *self-assessed health* (1 to 5)

MLE results Mean Variance

Step 2: uncertainty about own health dynamics with age

Model

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- Initial beliefs $N(\hat{\delta}_{i0}, \hat{\sigma}_0^2)$ (at $t = 0$),
  - Initial bias $b = \mathbb{E}(\hat{\delta}_{i0} - \delta_i)$
  - Initial uncertainty $\lambda = \frac{\hat{\sigma}_0}{\sigma_\delta}$

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- Posterior beliefs $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ with recursive updating equations

equations

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Empirical Strategy

- For identification, use *Subjective Survival Expectations*
  - *What is the percentage chance you will live to be (80, 85, 90, 95 or 100) or more?* $(plive10)$

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- From the model, survival expectations depend on beliefs about future health

$$\widehat{plive10}_{it} = f_S(h_{it}, \hat{\delta}_{it}, \hat{\sigma}_t^2, \alpha_i)$$

where beliefs $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ depend on initial bias b and uncertainty λ

descriptive link

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- Simulation shows
  - $\mathbb{E}(plive10_{it})$ depends on bias b
  - $Cov(\Delta plive10_{it}, \Delta h_{it}) \approx$ persistence component (ρ) + learning component (λ)

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- Identification does not rely on relation between beliefs and working decision

simulation strategy | simulation figures | ident. w/subj survival rates

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Results Fit Magnitudes

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- In any model, the working decision rule p_{it} is a function of the information set at that point, Ω_{it-1}.

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  - However, probit results assume a linear index and could be misspecified
- Instead, want to estimate this probability flexibly
  - Take advantage of neural networks for flexible estimation
  - Beliefs are unobserved to the econometrician
  - To deal with them, use an iterative approach based on EM algorithm

probit

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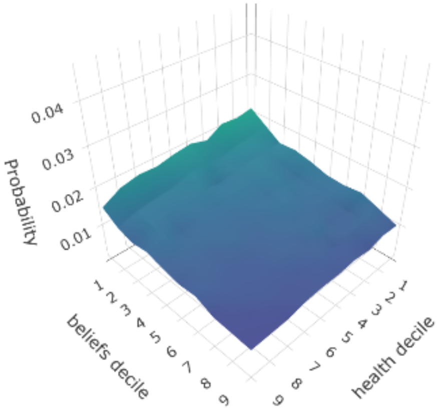
- It approximates very general functions, $\sim$ (complex) sieve estimation

figure NN details iterative strategy

Step 3: working decisions

Result: beliefs have a **positive** marginal effect

(1a) Avg marginal effect of $\hat{\delta}_{it-1}$ on $\mathbb{P}(p_{it} = 1)$ across individuals $p_{it-1} = 1$



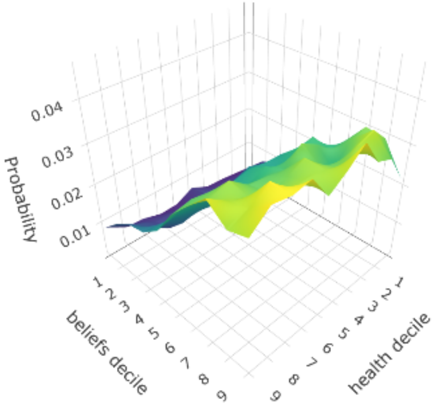
- $age_{it} \in [52, 59]$
- x-axis deciles of health h_{it-1}
- y-axis deciles of expected beliefs $\hat{\delta}_{it-1}$
- z-axis is $\mathbb{E}\left(\frac{\partial \mathbb{P}(p_{it}=1)}{\partial \hat{\delta}_{it-1}}\right)$
- Avg probability 80-90 pp

loss | fit | mg effect of $\hat{\delta}_{it}$ | mg effect of h_{it} | IRF | Decomposition

Step 3: working decisions

Result: **non-linear** effects of beliefs for younger older adults not working

(1b) Avg marginal effect of $\hat{\delta}_{it-1}$ on $\mathbb{P}(p_{it} = 1)$ across individuals $p_{it-1} = 0$



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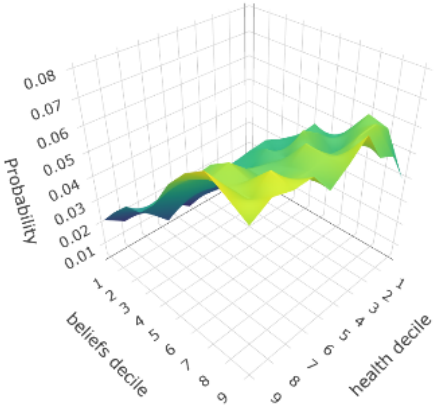
- Avg probability 10-30 pp

loss | fit | mg effect of $\hat{\delta}_{it}$ | mg effect of h_{it} | IRF | Decomposition

Step 3: working decisions

Result: **interaction** effects for younger older adults not working

(1c) Avg marginal effect of h_{it-1} on $\mathbb{P}(p_{it} = 1)$ across individuals $p_{it-1} = 0$



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    - Heterogeneous slopes with age help explain increasing variance
- Individuals are uncertain about own health dynamics, and negatively biased
    - Individuals believe their health will deteriorate faster with age
    - Individuals believe their survival probabilities are lower
- Older adults' working decisions depend on their beliefs
    - Positive marginal effects of better expected health
    - Better expected health matters particularly for younger adults not working
    - Eliminating the bias would increase participation by more than 2 pp

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- These results open a door for policies providing information to have an effect
- On one such policy is information about cholesterol and blood glucose levels
  - Testable in HRS due to randomization on biomarker's collection
  - But this additional information is not enough to generate changes
- Other larger signals potentially could
  - Information campaigns about survival at the population level
  - Biomarkers on kidney function and systemic inflammation
  - Genetic information

Thank you!

Appendix

Data and preliminaries

Health measures

- Chronic conditions: high blood pressure, heart attack, diabetes, stroke, lung disease, arthritis, cancer
- Self reported health: excellent, very good, good, fair, poor
- Body mass index
- Eyesight in general, at a distance, and up close: excellent, very good, good, fair, poor and legally blind
- Hearing: excellent, ... poor
- Pain: no pain, mild, moderate and severe pain
- ADLs mobility: walk 1 block, several blocks, across room, climb 1 flight of stairs, several flight of stairs
- ADLs large muscles: push or pull large object, sit for 2 hours, get up from chair, stoop kneel or crouch
- Other ADLs: carry 10 lbs, reach arms

back

Data and preliminaries

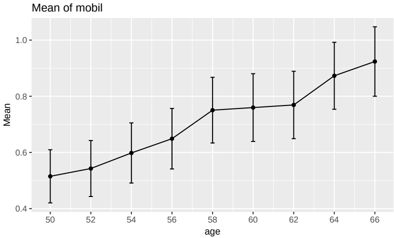
Confirmatory Factor Analysis results

Measure of health	Intercept	Loading	R-squared
Number of chronic conditions$^{(a)}$	0	1	0.29
Self-assessed health	8.188	-1.027	0.44
Body mass index	37.278	-1.812	0.05
Eyesight in general	5.710	-0.549	0.15
Eyesight at a distance	5.177	-0.502	0.13
Eyesight up close	5.465	-0.523	0.13
Hearing	4.830	-0.424	0.08
Pain	4.792	-0.802	0.36
Difficulties in ADLs regarding mobility	9.398	-1.598	0.64
Difficulties in ADLs of large muscles	8.964	-1.475	0.63
Difficulties in other ADLs	3.812	-0.654	0.50

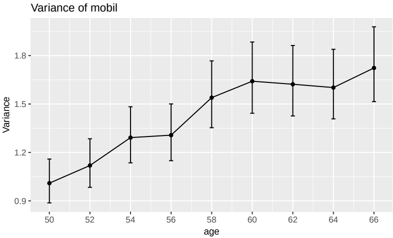
Note: (a) The first measure corresponds to 7 minus the number of chronic conditions, hence, larger values represent better health. For this variable, the intercept and loading are fixed to 0 and 1, respectively. All other coefficients are significant at 1%.

back

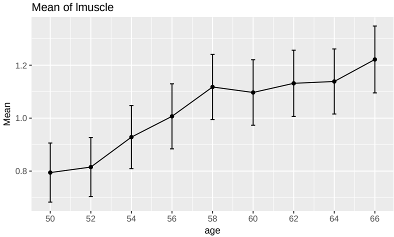
Mean and variance of each health measure with age



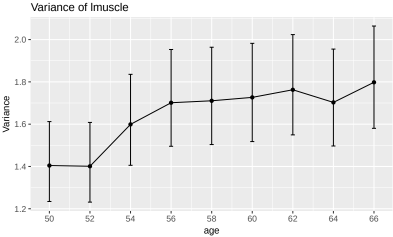
(a) Mean ADL mobility



(b) Var ADL mobility



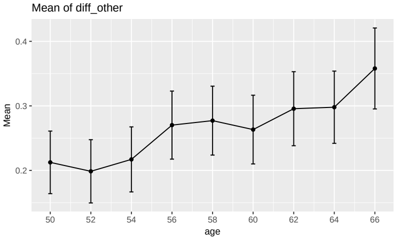
(c) Mean ADL large muscles



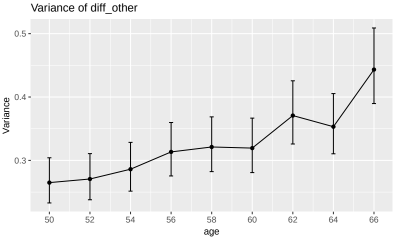
(d) Var ADL large muscles

back

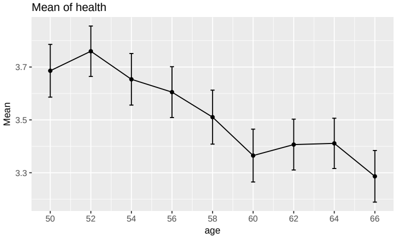
Mean and variance of each health measure with age



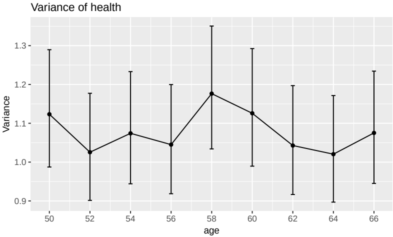
(a) Mean other ADLs



(b) Var other ADLs



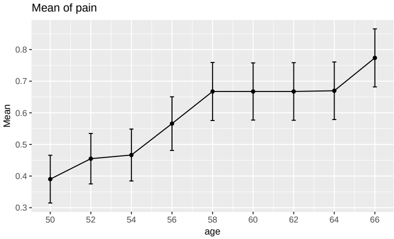
(c) Mean self reported health



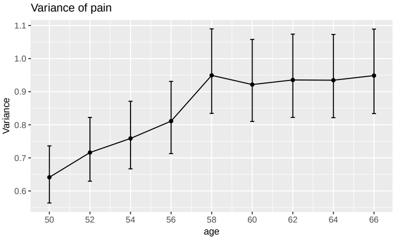
(d) Var self reported health

back

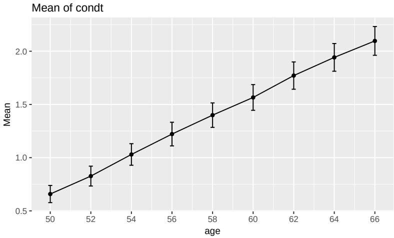
Mean and variance of each health measure with age



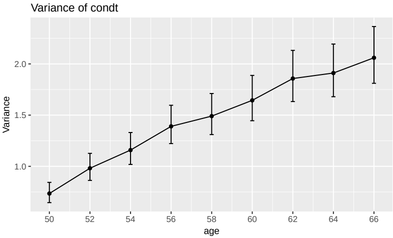
(a) Mean pain



(b) Var pain

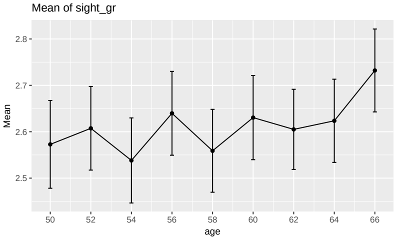


(c) Mean chronic conditions

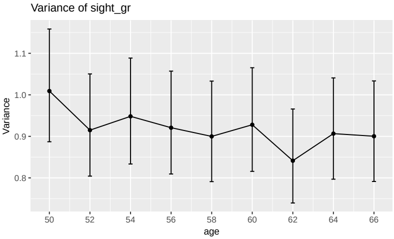


(d) Var chronic conditions

Mean and variance of each health measure with age

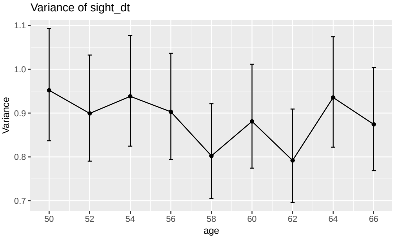


(a) Mean sight in general



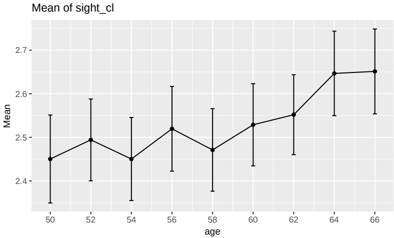
(b) Var sight in general

(c) Mean sight at a distance

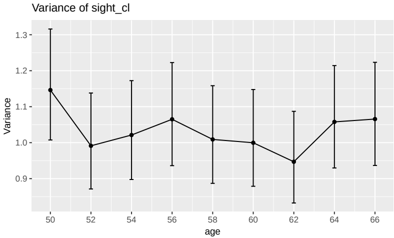


(d) Var sight at a distance

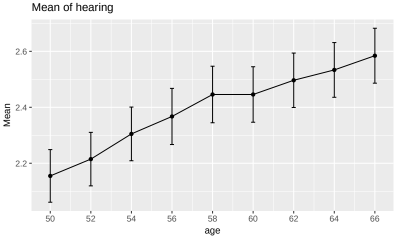
Mean and variance of each health measure with age



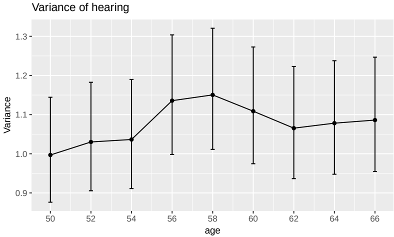
(a) Mean sight up close



(b) Var sight up close



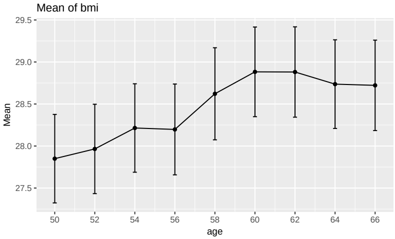
(c) Mean hearing



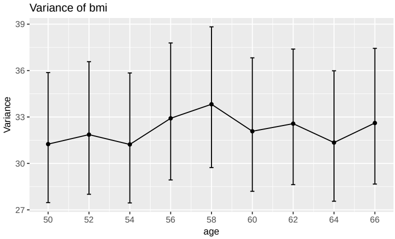
(d) Var hearing

back

Mean and variance of each health measure with age



(a) Mean BMI



(b) Var BMI

back

Step 1: heterogeneous health dynamics

Health and survival equations

Health equation:

$$h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \tau t^2 + \epsilon_{it}$$

Survival equation:

$$S_{it} \quad = \quad \mathbb{1}\left\{\gamma h_{it-1} + \theta_0 + \theta_1 \cdot t + \theta_2' x_i + \iota_1 \alpha_i + \iota_2 \delta_i + \iota_3 t \alpha_i + \iota_4 t \delta_i + \eta_{it} \geq 0\right\} S_{it-1}$$

Unobservables:

$$\left(\begin{array}{c} \alpha_i \\ \delta_i \end{array} \right) \Bigg| x_i, h_{i0} \quad \sim \quad N\left(\left(\begin{array}{c} \mu_\alpha + \nu_\alpha' x_i + \omega_\alpha h_{i0} \\ \mu_\delta + \nu_\delta' x_i + \omega_\delta h_{i0} \end{array} \right), \left[\begin{array}{cc} \sigma_\alpha^2 & \phi \sigma_\alpha \sigma_\delta \\ \phi \sigma_\alpha \sigma_\delta & \sigma_\delta^2 \end{array} \right] \right)$$

$\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$, $\eta_{it} \sim N(0, 1)$ are serially independent and independent of each other

back

Step 1: heterogeneous health dynamics

Likelihood

Random coefficient model

$$log\Big(\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mathbb{P}\big(h_{i1},S_{i1},\dots h_{iT_i},S_{iT_i}|x_i,h_{i0},\alpha,\delta\big)\cdot\phi_{\alpha,\delta}(\alpha,\delta|x_i,h_{i0})d\alpha d\delta\Big)$$

$$=log\Big(\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\prod_{t=1}^{T_i-1}\mathbb{P}\big(S_{it}=1|h_{it-1},S_{it-1},\alpha,\delta\big)\cdot\mathbb{P}\big(h_{it}|h_{it-1},S_{it}=1,\alpha,\delta\big)$$

$$\cdot\mathbb{P}\big(S_{iT_i}=0|h_{iT_i-1},S_{iT_i-1}=1,\alpha,\delta\big)\phi_{\alpha,\delta}(\alpha,\delta|x_i,h_{i0})d\alpha d\delta\Big)$$

back

Step 1: heterogeneous health dynamics

MLE results on health and survival

	Symbol	Coefficient	Pvalue
Persistence	ρ	0.223	0.000
Mean* of α_i	μ_α	0.955	0.000
Mean* of δ_i	μ_δ	-0.057	0.018
SD of α_i	σ_α	0.235	0.000
SD of δ_i	σ_δ	0.043	0.000
$Corr(\alpha_i, \delta_i)$	ϕ	-0.033	0.714
SD of health shocks	σ_ϵ	0.266	0.000
Survival dependence on health	γ	0.583	0.001
Controls		Yes	
N alive observations		8,901	
N dead observations		112	
N individuals		1,671	
-Log likelihood		3,027.6	

Hence, evidence of slope heterogeneity

3 versions back

Step 1: heterogeneous health dynamics

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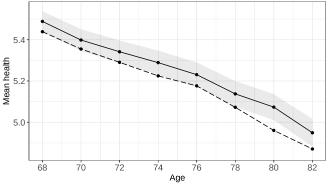
Hence, evidence of slope heterogeneity

3 versions back

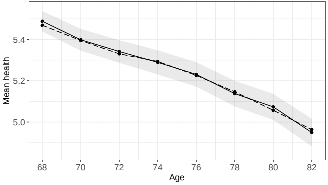
Step 1: heterogeneous health dynamics

Fit under different assumptions

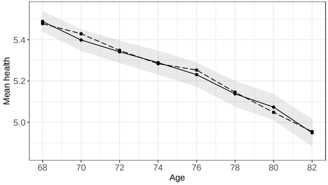
Figure: Mean of health with age
(solid lines: data; dotted lines: predicted values)



(a) Heterogeneous slopes without survival equation



(b) Heterogeneous slopes and survival equation



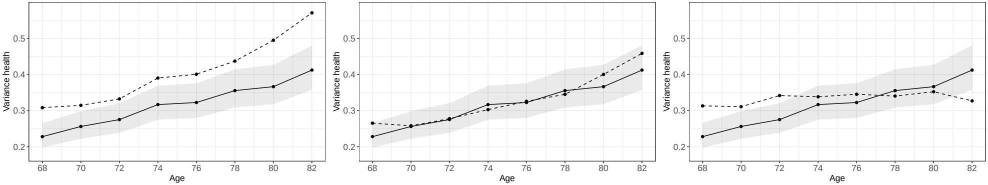
(c) Homogeneous slopes and survival equation

back

Step 1: heterogeneous health dynamics

Fit under different assumptions

Figure: Variance of health with age
(solid lines: data; dotted lines: predicted values)



(a) Heterogeneous slopes without survival equation

(b) Heterogeneous slopes and survival equation

(c) Homogeneous slopes and survival equation

Robustness checks:

- Heteroskedastic health shocks do not explain away slope heterogeneity
- Heterogeneous slopes also in a model for *self-assessed health* (1 to 5)

back

Step 1: heterogeneous health dynamics

MLE results: health equation

back

	Heterogeneous slopes without survival eq		Heterogeneous slopes with survival eq		Homogeneous slopes with survival eq	
	Coefficient (1)	Pvalue (2)	Coefficient (3)	Pvalue (4)	Coefficient (5)	Pvalue (6)
ρ	0.225	0.000	0.223	0.000	0.366	0.000
τ	0.001	0.087	0.001	0.119	0.001	0.108
μ_α	0.968	0.000	0.955	0.000	0.781	0.000
$\nu_{\alpha female}$	-0.029	0.132	-0.029	0.131	-0.024	0.163
$\nu_{\alpha white}$	0.026	0.338	0.027	0.335	0.018	0.458
$\nu_{\alpha hispanic}$	0.004	0.909	0.005	0.889	-0.001	0.973
$\nu_{\alpha less\_HS}$	-0.134	0.000	-0.134	0.000	-0.120	0.000
ω_α	0.599	0.000	0.603	0.000	0.492	0.000
μ_δ	-0.060	0.012	-0.057	0.018	-0.051	0.000
$\nu_{\delta female}$	0.006	0.146	0.006	0.136	0.005	0.198
$\nu_{\delta white}$	0.015	0.007	0.015	0.008	0.013	0.011
$\nu_{\delta hispanic}$	0.010	0.196	0.010	0.199	0.006	0.390
$\nu_{\delta less\_HS}$	-0.003	0.677	-0.003	0.624	0.001	0.896
ω_δ	0.000	0.956	0.000	0.962		
σ_α	0.235	0.000	0.235	0.000	0.212	0.000
σ_δ	0.042	0.000	0.043	0.000		
ϕ	-0.030	0.741	-0.033	0.714		
σ_ϵ	0.266	0.000	0.266	0.000	0.285	0.000

Step 1: heterogeneous health dynamics

MLE results: survival equation

back

	Heterogeneous slopes without survival eq		Heterogeneous slopes with survival eq		Homogeneous slopes with survival eq	
	Coefficient (1)	Pvalue (2)	Coefficient (3)	Pvalue (4)	Coefficient (5)	Pvalue (6)
γ			0.583	0.001	0.640	0.000
ι_1			-0.277	0.334	-0.422	0.125
ι_2			0.044	0.986		
ι_3			0.029	0.306	0.036	0.287
ι_4			0.241	0.601		
θ_0			0.529	0.326	0.514	0.336
θ_1			-0.178	0.136	-0.193	0.092
$\theta_{2female}$			0.259	0.002	0.255	0.002
θ_{2white}			0.019	0.847	0.029	0.758
$\theta_{2hispanic}$			0.317	0.079	0.311	0.078
θ_{2less_HS}			-0.106	0.305	-0.114	0.267
N alive observations	8,901		8,901		8,901	
N dead observations	0		112		112	
N individuals	1,671		1,671		1,671	
-LL	2,498.6		3,027.6		3,067.6	

Step 2: uncertainty about own health dynamics with age

Bayes' updating equations

Posterior variance

$$\frac{1}{\hat{\sigma}_t^2} = \frac{1}{\hat{\sigma}_{t-1}^2} + \frac{t^2}{\sigma_\epsilon^2}$$

Posterior mean

$$\begin{aligned} \frac{\hat{\delta}_{it}}{\hat{\sigma}_t^2} &= \frac{\hat{\delta}_{it-1}}{\hat{\sigma}_{t-1}^2} + \frac{(h_{it} - \rho h_{it-1} - \alpha_i)t}{\sigma_\epsilon^2} \\ \Leftrightarrow \hat{\delta}_{it} &= \hat{\delta}_{it-1} + K_t(\lambda, \sigma_\epsilon^2) \cdot \hat{\zeta}_{it} \end{aligned}$$

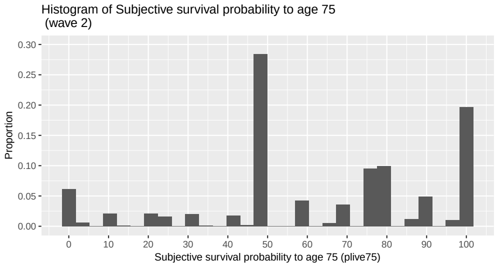
where

- $\hat{\zeta}_{it}$ is the perceived innovation in health, $\hat{\zeta}_{it} \equiv h_{it} - \mathbb{E}(h_{it}|\Omega_{it-1})$
- $K_t(\lambda = 0, \sigma_\epsilon^2) = 0$, $\frac{\partial K_t}{\partial \lambda} > 0$, and $\frac{\partial K_t}{\partial \sigma_\epsilon^2} < 0$

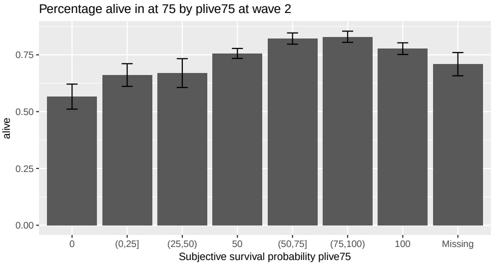
back

Step 2: uncertainty about own health dynamics with age

Subjective survival probabilities in the HRS



(a) Histogram of plive75 (wave 2, $age \leq 65$)

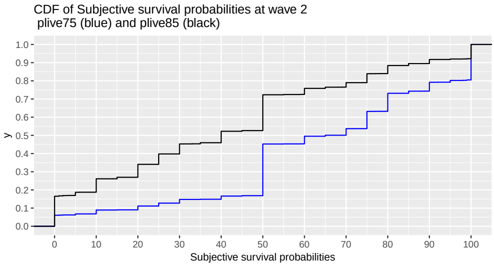


(b) Percentage alive at 75 by plive75 at wave 2

back

Step 2: uncertainty about own health dynamics with age

Subjective survival probabilities in the HRS (cont.)

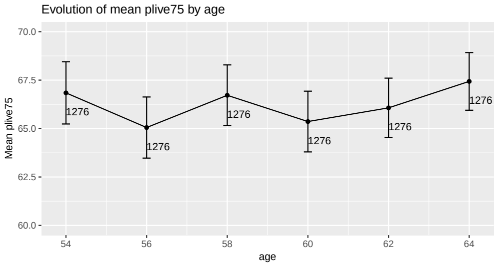


(a) Cumulative distribution of plive75 and plive85 (wave 2, $age \leq 75$)

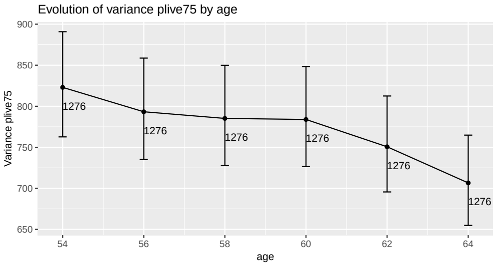
back

Step 2: uncertainty about own health dynamics with age

Subjective survival probabilities in the HRS (cont.)



(a) Mean of plive75 with age



(b) Variance of plive75 with age

back

Step 2: uncertainty about own health dynamics with age

Link with subjective **survival probabilities**

What is the percentage chance you will live to be (80, 85, 90, 95 or 100) or more? ($plive10_{it}$)

Let s denote the reference age asked in $plive10_{it}$

$$
\begin{aligned}
plive10_{it} &= \mathbb{P}(S_{is} = 1 | \Omega_{it}) = \prod_{l=t}^{s-1} \mathbb{P}(S_{il+1} = 1 | S_{il}, \Omega_{it}) \\
&= \prod_{l=t}^{s-1} \mathbb{P}(\gamma h_{il} + \eta_{il+1} \geq 0 | \Omega_{it})
\end{aligned}
$$

where

$$h_{il}(\Omega_{it}) = h_{il}(h_{it}, \hat{\delta}_{it}, \hat{\sigma}_t^2, \alpha_i) \text{ random variable}$$

$$\Rightarrow \quad plive10_{it} = \mathbb{P}(S_{is} = 1 | h_{it}, \hat{\delta}_{it}, \hat{\sigma}_t^2, \alpha_i)$$

back

Step 2: uncertainty about own health dynamics with age

Link with subjective **survival probabilities**

From the equation for the health process,

$$h_{il} \quad = \quad \rho h_{il-1} + \alpha_i + \delta_i \cdot l + \epsilon_{il}$$

Applying this equation recursively,

$$h_{il} \quad = \quad \underbrace{\rho^{l-t} h_{it} + \alpha_i \sum_{k=0}^{l-t-1} \rho^k}_{\text{known under } \Omega_{it}} + \underbrace{\delta_i \sum_{k=0}^{l-t-1} (l-k)\rho^k + \sum_{k=0}^{l-t-1} \rho^k \epsilon_{i(l-k)}}_{\text{unknown under } \Omega_{it}}$$

From the view point of Ω_{it},

$$\delta_i \sim N(\hat{\delta}_{it}, \hat{\sigma}_t^2), \qquad \epsilon_{i(l-k)} \sim N(0, \sigma_\epsilon^2) \text{ iid}$$

where $\hat{\delta}_{it} = \hat{\delta}_{it}(b, \lambda)$, $\hat{\sigma}_t^2 = \hat{\sigma}_t^2(\lambda)$

back

Step 2: uncertainty about own health dynamics with age

Strategy for estimating bias b and uncertainty λ when $t_0 = 0$

- Goal: simulate $plive10(\alpha_i, \hat{\delta}_{i0}, h_{i0}, \dots h_{iT}, b, \lambda)$ to estimate b and λ

- But distribution of $\hat{\delta}_{i0}$ depends on λ and b

- Steps
  - Draw α_i, δ_i conditional on $h_{i0}, \dots h_{iT}$
  - For a given b and λ,
    - Set $\hat{\sigma}_0^2 = \lambda^2 \sigma_\delta^2$
    - Draw $\hat{\delta}_{i0}$ conditional in $\alpha_i, \delta_i, h_{i0}$
    - Use α_i, $\hat{\delta}_{i0}$ and h_i^T to simulate $\widehat{plive10}_{it}$
    - Compare the distance between the empirical moments with the simulated ones

back

Step 2: uncertainty about own health dynamics with age

Strategy for estimating bias b and uncertainty λ when $t_0 > 0$

- Goal: simulate $plive10(\alpha_i, \hat{\delta}_{it_0}, h_{it_0}, \ldots h_{iT}, b, \lambda)$ to estimate b and λ

- But distribution of $\hat{\delta}_{it_0}$ is not random conditional on λ and b

- It holds that

$$\hat{\delta}_{it_0} = \hat{\delta}_{it_0}(\underbrace{h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2}, \hat{\delta}_{i0}}_{\substack{\text{unobserved by} \\ \text{the econometrician}}}, h_{it_0}; \lambda)$$

where T_{i1} and T_{i2} are functions of past health shocks

back

Step 2: uncertainty about own health dynamics with age

Strategy for estimating bias b and uncertainty λ when $t_0 > 0$ (cont.)

$$\hat{\delta}_{it_0} = K_{t_0}(\lambda)\Bigg[-\rho^{t_0} h_{i0} - \alpha_i \sum_{k=0}^{t_0-1} \rho^k + \delta_i \left(\frac{1}{t_0} \sum_{l=1}^{t_0-1} l^2 - \sum_{k=1}^{t_0-1} (t_0 - k)\rho^k \right)$$

$$-\rho T_{i1} + T_{i2}\frac{1}{t_0} + \left(h_{it_0} - \gamma \sum_{k=0}^{t_0-1} (t_0-k)^2 \rho^k \right) \Bigg] + \hat{\delta}_{i0} \frac{\sigma_\epsilon^2}{\lambda^2 \sigma_\delta^2} \frac{K_{t_0}(\lambda)}{t_0}$$

where

$$T_{i1} = \sum_{l=1}^{t_0-1} \rho^{t_0-1-l} \epsilon_{il}, \qquad T_{i2} = \sum_{l=1}^{t_0-1} l \epsilon_{il}$$

back

Step 2: uncertainty about own health dynamics with age

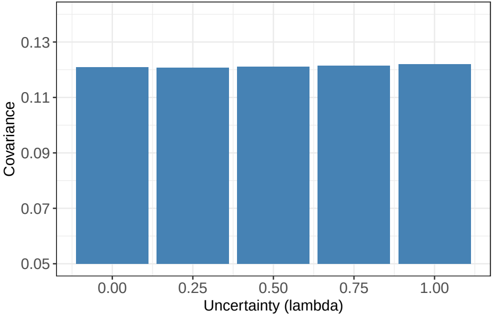
Strategy for estimating bias b and uncertainty λ when $t_0 > 0$ (cont.)

- Hence, given $h_{it_0}, \ldots h_{iT}$, I first get draws of $(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2})$
- Having survived up to t_0 further restricts $(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2})$
- No closed form solution $\Rightarrow$ use MCMC
- Then, for a given b and and λ
  - Set $\hat{\sigma}^2_{t_0} = \sigma(\lambda, \sigma^2_\delta, t_0)$
  - Draw $\hat{\delta}_{i0}$ conditional on $\alpha_i, \delta_i, h_{i0}$
  - Use $\hat{\delta}_{i0}$ and $(h_{i0}, \alpha_i, \delta_i, T_{i1}, T_{i2})$ to construct $\hat{\delta}_{it_0}$
  - Use α_i, $\hat{\delta}_{it_0}$ and $h_{it_0}, \ldots h^T_i$ to simulate $\widehat{plive10}_{it}$
  - Compare the distance between the empirical moments with the simulated ones
- Target moments of averages across time for given t_0

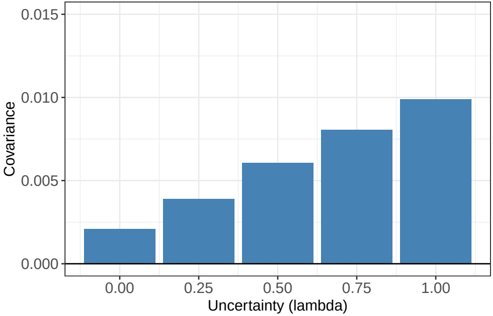
back

Step 2: uncertainty about own health dynamics with age

Simulated covariance moments of Survival Expectations as function of uncertainty λ



(a) $Cov(plive10, h)$



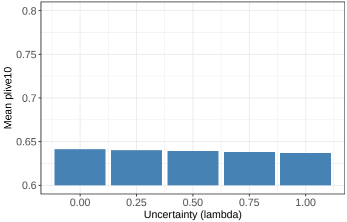
(b) $Cov(\Delta plive10, \Delta h)$

back

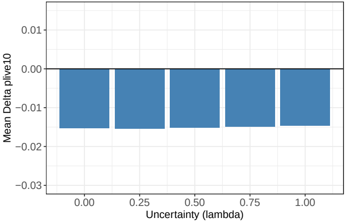
Step 2: uncertainty about own health dynamics with age

Simulated moments of Survival Expectations as function of uncertainty λ

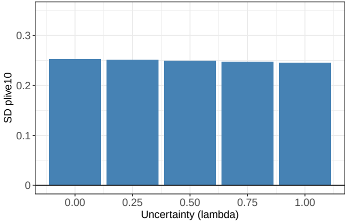
back



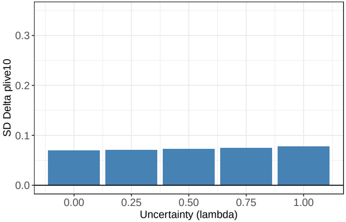
(a) Mean $plive10$



(b) Mean $\Delta plive10$



(c) SD $plive10$

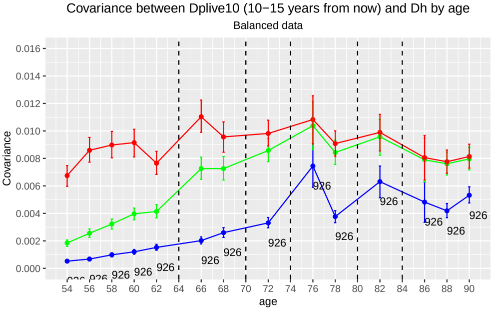


(d) SD $\Delta plive10$

Step 2: uncertainty about own health dynamics with age

Simulated $Cov(\Delta plive10, \Delta h)$ for different values of uncertainty λ

Figure: $Cov(\Delta plive10, \Delta h)$ for different values of uncertainty λ by age



Note: red $\lambda = 1$, green $\lambda = 0.5$, blue=0

back

Step 2: uncertainty about own health dynamics with age

Identification with subjective **survival rates**

We could identify λ with panel data on expectations about **survival rates**

$$\begin{aligned} bsr_{it} &= \mathbb{P}(S_{it+3} = 1 | S_{it+2} = 1, \Omega_{it}) \\ bsr_{it+1} &= \mathbb{P}(S_{it+3} = 1 | S_{it+2} = 1, \Omega_{it+1}) \end{aligned}$$

Then,

$$\Delta_w \Phi^{-1} bsr_{it+1} = \underbrace{\rho(h_{it+1} - \rho h_{it} - \alpha_i - \hat{\delta}_{it}(t+1))}_{\text{due to persistence } \rho} + \underbrace{(t+2)(\hat{\delta}_{it+1} - \hat{\delta}_{it})}_{\text{due to learning } \lambda}$$

And

$$\Rightarrow Cov(\Delta_w \Phi^{-1} bsr_{it+1}, \Delta h_{it+1}) = C_t(\lambda) \cdot Var(\Delta h_{it+1})$$

where $C_t(\lambda)$ is increasing in λ back

Step 2: uncertainty about own health dynamics with age

Results

	Symbol	Coefficient	Lower bound	Upper bound
Bias	b	-0.061	-0.061	-0.060
Uncertainty	λ	0.338	0.336	0.340
Mean of measurement error	μ_{merror}	0.121	0.118	0.123
SD of measurement error	σ_{merror}	0.177	0.176	0.177

Note: The simulation includes non-classical measurement error $\nu_{it} \sim N(\mu_{merror}, \sigma^2_{merror})$ with observed values are $max\{min\{plive10_{it} + \nu_{it}, 1\}, 0\}$. Standard errors clustered at the individual level

back

Step 2: uncertainty about own health dynamics with age

SMM fit

$\approx$ Target moments

	Data moment	SE	Simulated moment
$\mathbb{E}(plive10)$	0.531	(0.00011)	0.538
$\mathbb{E}(plive10^2)$	0.371	(0.00012)	0.357
$\mathbb{E}(plive10 \cdot h)$	2.890	(0.00065)	2.957
$\mathbb{E}(\Delta plive10)$	-0.013	(0.00002)	-0.014
$\mathbb{E}((\Delta plive10)^2)$	0.070	(0.00003)	0.066
$\mathbb{E}(\Delta plive10 \Delta h)$	0.007	(0.00002)	0.007

Note: same sample used for estimation

Other moments

	Data moment	SE	Simulated moment
$\mathbb{E}(plive75)$	0.702	(0.00017)	0.806
$\mathbb{E}(plive75^2)$	0.556	(0.00021)	0.687
$\mathbb{E}(plive75 \cdot h)$	3.886	(0.00101)	4.469
$\mathbb{E}(\Delta plive75)$	-0.001	(0.00010)	0.018
$\mathbb{E}((\Delta plive75)^2)$	0.054	(0.00008)	0.042
$\mathbb{E}(\Delta plive75 \Delta h)$	0.006	(0.00005)	0.003

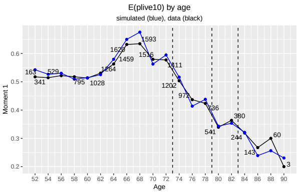
Note: subsample used for estimation that is also under 65 years old, $N = 1,247$ individuals

back

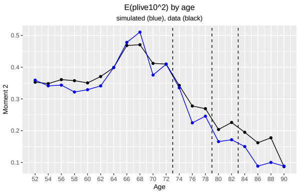
Step 2: uncertainty about own health dynamics with age

SMM Fit back

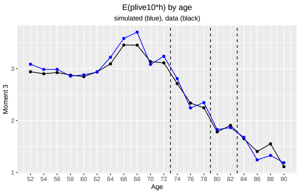
Figure: Moments' fit by age (data (black), model (blue))



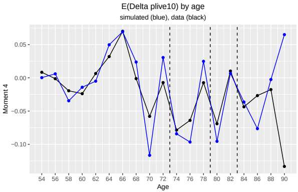
(a) $\mathbb{E}(plive10)$



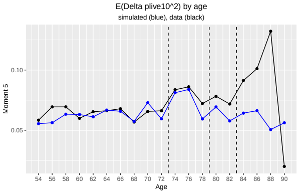
(b) $\mathbb{E}(plive10^2)$



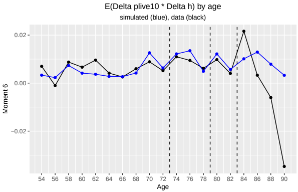
(c) $\mathbb{E}(plive10 \cdot h)$



(d) $\mathbb{E}(\Delta plive10)$



(e) $\mathbb{E}(\Delta^2 plive10)$



(f) $\mathbb{E}(\Delta plive10 \cdot \Delta h)$

Step 2: uncertainty about own health dynamics with age

Magnitudes in context

back

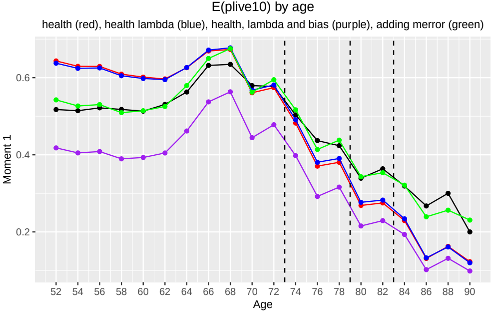


Figure: Observed and simulated $E(plive10)$ under different assumptions

Step 3: working decisions

In a model with heterogeneous and uncertain health dynamics

p_{it} labor participation, c_{it} consumption

$$V_t(\Omega_{it-1}) = \max_{p_{it}, c_{it}} \Bigg\{ \mathbb{E}\Bigg(\overbrace{U(p_{it}, c_{it}, h_{it}, p_{it-1})}^{\text{flow utility}} \Bigg| \Omega_{it-1} \Bigg) + \beta \mathbb{E}\Bigg(\underbrace{S_{it+1}}_{\text{survival}} V_{t+1}(\Omega_{it}) + (1 - S_{it+1}) \underbrace{B(a_{it})}_{\text{bequest}} \Bigg| \Omega_{it-1}, p_{it}, c_{it} \Bigg) \Bigg\}$$

st.

- Budget constraint, with assets $a_{it} = a(\Omega_{it-1}, p_{it}, c_{it}, h_{it}, w_{it})$
- Health process $h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it}$
- Beliefs about δ_i following $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ defined by updating equations

Step 3: working decisions

In a model with heterogeneous and uncertain health dynamics

p_{it} labor participation, c_{it} consumption

$$V_t(\Omega_{it-1}) = \max_{p_{it},c_{it}} \left\{ \mathbb{E}\left(\overbrace{U(p_{it}, c_{it}, h_{it}, p_{it-1})}^{\text{flow utility}} \middle| \Omega_{it-1} \right) + \beta \mathbb{E}\left(\underbrace{S_{it+1}}_{\text{survival}} V_{t+1}(\Omega_{it}) + (1 - S_{it+1}) \underbrace{B(a_{it})}_{\text{bequest}} \middle| \Omega_{it-1}, p_{it}, c_{it} \right) \right\}$$

st.

- Budget constraint, with assets $a_{it} = a(\Omega_{it-1}, p_{it}, c_{it}, h_{it}, w_{it})$
- Health process $h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it}$ heterogeneity
- Beliefs about δ_i following $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$
  defined by updating equations

Step 3: working decisions

In a model with heterogeneous and uncertain health dynamics

p_{it} labor participation, c_{it} consumption

$$V_t(\Omega_{it-1}) = \max_{p_{it}, c_{it}} \Bigg\{ \mathbb{E}\Bigg(\overbrace{U(p_{it}, c_{it}, h_{it}, p_{it-1})}^{\text{flow utility}} \Bigg| \Omega_{it-1} \Bigg) +$$

$$\beta \mathbb{E}\Bigg(\underbrace{S_{it+1}}_{\text{survival}} V_{t+1}(\Omega_{it}) + (1 - S_{it+1}) \underbrace{B(a_{it})}_{\text{bequest}} \Bigg| \Omega_{it-1}, p_{it}, c_{it} \Bigg) \Bigg\}$$

st.

- Budget constraint, with assets $a_{it} = a(\Omega_{it-1}, p_{it}, c_{it}, h_{it}, w_{it})$
- Health process $h_{it} = \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it}$
- Beliefs about δ_i following $N(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ defined by updating equations

incomplete information

Step 3: working decisions

In a model with heterogeneous and uncertain health dynamics

Information set

$$\Omega_{it-1} \quad = \quad \{t, p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i\}$$

Step 3: working decisions

In a model with heterogeneous and uncertain health dynamics

Information set

$$\Omega_{it-1} = \{t, p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i\}$$

Policy rule for working decision

$$p_{it} = p(t, p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i)$$

Step 3: working decisions

In a model with heterogeneous and uncertain health dynamics

Information set

$$\Omega_{it-1} \quad = \quad \{t, p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i\}$$

Policy rule for working decision

$$p_{it} \quad = \quad p(t, p_{it-1}, a_{it-1}, w_{it-1}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i)$$

- Survival expectations $plive10_{it}$ help us identify $\hat{\delta}_{it}$ and $\hat{\sigma}^2_t$
- Conditional on Ω_{it-1}, $plive10_{it}$ do not play a role on decisions p_{it}

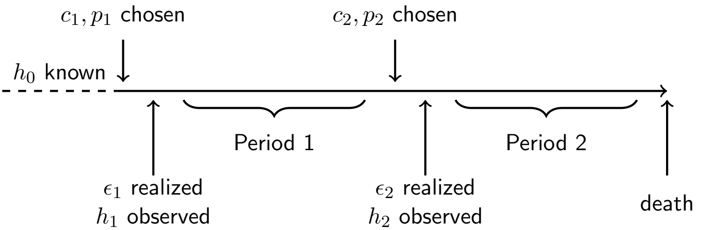
Step 3: working decisions

A simple two-period model for building intuition

$$\max_{p_1,p_2,c_1,c_2 \in \{\{0,1\}^2,\mathbb{R}^2\}} \quad \mathbb{E}(U_1(c_1,p_1,h_1) + \beta U_2(c_2,p_2,h_2)|h_0)$$

st

Preferences	$U_k(c_k,p_k,h_k) = ln(c_k) - \tau(1-h_k)p_k$
Health process	$h_k = h_{k-1} + \delta + \epsilon_k, \quad \epsilon_k \sim N(0,\sigma_\epsilon^2) iid$
Budget constraint	$c_k = s + w \cdot (1 - \nu(1-p_{k-1})) \cdot p_k,$



Case 1: no uncertainty in δ

$$p_1(h_0;\delta) = \mathbb{1}\{h_0 \geq h_1^*(\delta)\}$$

Case 2: adding uncertainty in δ

Assuming prior beliefs over $\delta \sim N(\delta_0, \sigma_0^2)$, updated according to Bayes' rule, then

$$p_1(h_0, \delta_0, \sigma_0^2) = \mathbb{1}\{h_0 \geq \tilde{h}_1(\delta_0, \sigma_0^2)\}$$

satisfying that

- $\tilde{h}_1(\delta_0, \sigma_0^2)$ is decreasing in δ_0 and σ_0^2
- $lim_{\delta_0 \to \delta, \sigma_0^2 \to 0} \tilde{h}_1(\delta_0, \sigma_0^2) = h_1^*(\delta)$

Step 3: working decisions

Probit results on $\mathbb{P}(p_{it} = 1 | \Omega_{it-1})$

Posterior variance | likelihood | Full results | back

		(1)		(2)		(3)	
		coeff	se	coeff	se	coeff	se
age	t	-0.20***	(0.016)	-0.08***	(0.003)	-0.19***	(0.016)
lagged work	p_{it-1}	2.03***	(0.018)	2.03***	(0.019)	2.03***	(0.019)
lagged health	h_{it-1}	0.17***	(0.024)	0.26***	(0.033)	0.18***	(0.046)
heterogeneous intercept	α_i	0.24***	(0.036)	0.07	(0.046)	0.24***	(0.075)
beliefs mean	$\hat{\delta}_{it-1}$	1.93***	(0.249)			1.90***	(0.499)
beliefs var	$\hat{\sigma}^2_{t-1}/\sigma^2_\delta$	-13.85***	(2.048)			-13.33***	(2.102)
survival expectations	$plive10_{it}$			0.11***	(0.031)	0.01	(0.043)
Controls	other vars Ω_{it-1}	Yes		Yes		Yes	
N individuals		14,969		14,718		14,718	
N observations		58,040		55,592		55,592	

Note: Standard errors are clustered at the individual level.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

- Beliefs are unobserved to econometrician and hence are integrated out

Step 3: working decisions

Probit results on $\mathbb{P}(p_{it} = 1|\Omega_{it-1})$

Posterior variance | likelihood | Full results | back

		(1)		(2)		(3)	
		coeff	se	coeff	se	coeff	se
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- Beliefs are unobserved to econometrician and hence are integrated out
- Beliefs matter: larger $\hat{\delta}_{it}$ implies larger probabilities of work

Step 3: working decisions

Probit results on $\mathbb{P}(p_{it} = 1|\Omega_{it-1})$

Posterior variance | likelihood | Full results | back

		(1)		(2)		(3)	
		coeff	se	coeff	se	coeff	se
age	t	-0.20***	(0.016)	-0.08***	(0.003)	-0.19***	(0.016)
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survival expectations	$plive10_{it}$			0.11***	(0.031)	0.01	(0.043)
Controls	other vars Ω_{it-1}	Yes		Yes		Yes	
N individuals		14,969		14,718		14,718	
N observations		58,040		55,592		55,592	

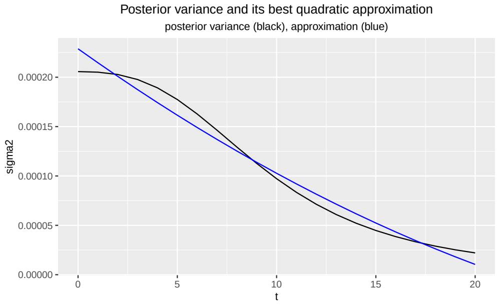
Note: Standard errors are clustered at the individual level.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

- Beliefs are unobserved to econometrician and hence are integrated out
- Beliefs matter: larger $\hat{\delta}_{it}$ implies larger probabilities of work
- Survival expectations $plive10_{it}$ do not matter once we control for beliefs

Step 3: working decisions

Posterior variance

Figure: Posterior variance. Formula (black) and its best approximation using a polynomial of degree 2 (blue)



back

Step 3: working decisions

Probit likelihood

- Flow utility includes an additive iid taste shock $\xi_{it} \sim$ Normal
- Information set $\Omega_{it-1} = \{t, p_{it-1}, a_{it-1}, w_{it-1}, \xi_{it}, h_{it-1}, \hat{\delta}_{it-1}, \hat{\sigma}^2_{t-1}, \alpha_i\}$
- Define $\tilde{\Omega}_{it-1} = \Omega_{it-1} \setminus \{\xi_{it}\}$
- Estimated policy rule for working decision $p_{it}(\tilde{\Omega}_{it-1})$ is random
- Probit model $\mathbb{P}(p_{it} = 1) = \Phi\left(\beta' \tilde{\Omega}_{it-1}\right) =$

$$\Phi\left(\beta_0 + \beta_{0t} t + \beta_1 h_{it-1} + \underbrace{\beta_2 \hat{\delta}_{it-1} + \beta_3 \hat{\sigma}^2_{t-1} + \beta_4 \alpha_i}_{\text{unobserved to the econometrician}} + \beta_5 p_{it-1} + \beta_6 a_{it-1}\right)$$

back

Step 3: working decisions

Probit likelihood

- Likelihood of p_{it}, conditional on $\tilde{\Omega}_{it-1}$

$$L_{it}^c = \Phi\left(\beta'\tilde{\Omega}_{it-1}\right)^{p_{it}} \cdot \left(1 - \Phi\left(\beta'\tilde{\Omega}_{it-1}\right)\right)^{1-p_{it}}$$

- Likelihood of p_i^T, conditional on $T, h_i^T, \hat{\delta}_{i0}, \hat{\sigma}_0, \alpha_i, p_{i0}, a_{i0}$

$$L_i^c = \prod_t L_{it}$$

- Likelihood of p_i^T, conditional on $T, h_i^T, plive10_i^T, p_{i0}, a_{i0}$

$$L_i = \int L_i^c \cdot f(\alpha_i, \hat{\delta}_{i0} | h_i^T, plive10_i^T, p_{i0}, a_{i0}) d\alpha_i d\hat{\delta}_{i0}$$

- This assumes no other unobserved heterogeneity at the i-level

back

Step 3: working decisions

Full results

Table: Probit results on $\mathbb{P}(p_{it} = 1|\Omega_{it-1})$

	(1)				(2)				(3)			
	coeff	se	ci lower	ci upper	coeff	se	ci lower	ci upper	coeff	se	ci lower	ci upper
Main equation												
intercept	-0.564	(0.294)	-1.140	0.011	-0.693	(0.297)	-1.276	-0.111	-2.445	(0.098)	-2.637	-2.253
t	-0.196	(0.016)	-0.227	-0.166	-0.192	(0.016)	-0.223	-0.160	-0.082	(0.003)	-0.088	-0.077
work	2.032	(0.018)	1.995	2.068	2.034	(0.019)	1.997	2.071	2.031	(0.019)	1.994	2.068
health	0.169	(0.024)	0.123	0.216	0.175	(0.046)	0.084	0.266	0.261	(0.033)	0.196	0.325
educ LHS	-0.032	(0.020)	-0.071	0.008	-0.032	(0.022)	-0.074	0.010	-0.034	(0.021)	-0.076	0.008
MS married	-0.030	(0.040)	-0.109	0.048	-0.012	(0.041)	-0.093	0.069	-0.014	(0.041)	-0.094	0.067
MS divorce	0.053	(0.043)	-0.032	0.137	0.069	(0.045)	-0.018	0.157	0.064	(0.044)	-0.023	0.150
MS widow	0.012	(0.045)	-0.075	0.100	0.028	(0.046)	-0.062	0.118	0.029	(0.046)	-0.061	0.119
Q1 income	-0.283	(0.026)	-0.335	-0.231	-0.290	(0.027)	-0.343	-0.236	-0.294	(0.027)	-0.347	-0.241
Q2 income	-0.165	(0.022)	-0.209	-0.122	-0.165	(0.023)	-0.210	-0.121	-0.168	(0.023)	-0.212	-0.124
Q3 income	-0.105	(0.020)	-0.144	-0.066	-0.108	(0.020)	-0.148	-0.068	-0.112	(0.020)	-0.151	-0.072
Q1 wealth	0.176	(0.024)	0.129	0.223	0.187	(0.025)	0.138	0.236	0.181	(0.025)	0.133	0.230
Q2 wealth	0.112	(0.022)	0.069	0.155	0.117	(0.022)	0.073	0.161	0.112	(0.022)	0.068	0.156
Q3 wealth	0.027	(0.020)	-0.013	0.067	0.027	(0.021)	-0.013	0.068	0.025	(0.021)	-0.015	0.066
female	-0.037	(0.015)	-0.066	-0.007	-0.036	(0.016)	-0.067	-0.004	-0.048	(0.016)	-0.079	-0.018
alpha	0.244	(0.036)	0.173	0.314	0.243	(0.075)	0.096	0.389	0.074	(0.046)	-0.016	0.165
delta hat	1.933	(0.249)	1.446	2.421	1.903	(0.499)	0.926	2.881				
sigma2 t/sigma2 d	-13.854	(2.048)	-17.868	-9.840	-13.335	(2.102)	-17.455	-9.214				
plive10					0.007	(0.043)	-0.077	0.091	0.114	(0.031)	0.052	0.175

Step 3: working decisions

Full results

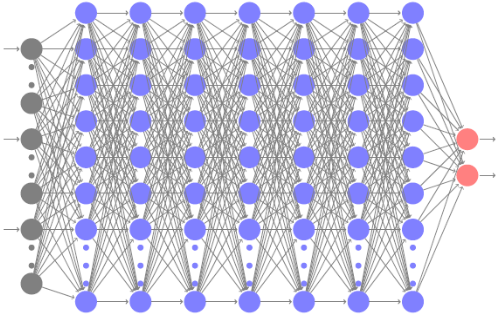
Table: Probit results on $\mathbb{P}(p_{it} = 1|\Omega_{it-1})$ (cont.) back

	(1)				(2)				(3)			
	coeff	se	ci lower	ci upper	coeff	se	ci lower	ci upper	coeff	se	ci lower	ci upper
Initial condition												
intercept	-2.840	(0.417)	-3.658	-2.023	-2.779	(0.419)	-3.601	-1.957	-1.583	(0.138)	-1.854	-1.313
t	-0.107	(0.022)	-0.149	-0.065	-0.106	(0.022)	-0.149	-0.062	-0.163	(0.004)	-0.171	-0.154
health	0.481	(0.040)	0.403	0.558	0.448	(0.083)	0.285	0.611	0.549	(0.058)	0.435	0.664
educ LHS	-0.059	(0.032)	-0.122	0.004	-0.038	(0.033)	-0.104	0.027	-0.040	(0.033)	-0.105	0.025
MS married	-0.276	(0.063)	-0.399	-0.152	-0.288	(0.063)	-0.412	-0.163	-0.297	(0.063)	-0.420	-0.174
MS divorce	0.055	(0.068)	-0.078	0.188	0.051	(0.069)	-0.084	0.185	0.045	(0.068)	-0.088	0.178
MS widow	0.023	(0.072)	-0.119	0.165	0.012	(0.073)	-0.131	0.155	0.008	(0.072)	-0.133	0.150
Q1 income	-1.201	(0.045)	-1.289	-1.113	-1.218	(0.046)	-1.308	-1.128	-1.227	(0.045)	-1.316	-1.138
Q2 income	-0.677	(0.039)	-0.754	-0.600	-0.703	(0.039)	-0.780	-0.625	-0.708	(0.039)	-0.785	-0.632
Q3 income	-0.413	(0.035)	-0.482	-0.345	-0.421	(0.035)	-0.490	-0.352	-0.426	(0.035)	-0.495	-0.357
Q1 wealth	0.709	(0.043)	0.626	0.793	0.703	(0.044)	0.618	0.789	0.695	(0.043)	0.611	0.779
Q2 wealth	0.512	(0.039)	0.437	0.588	0.513	(0.039)	0.437	0.590	0.507	(0.039)	0.432	0.583
Q3 wealth	0.249	(0.037)	0.177	0.321	0.255	(0.037)	0.182	0.328	0.253	(0.037)	0.181	0.325
female	-0.090	(0.025)	-0.139	-0.040	-0.079	(0.026)	-0.130	-0.027	-0.097	(0.026)	-0.148	-0.047
alpha	0.200	(0.057)	0.089	0.310	0.249	(0.126)	0.002	0.496	0.057	(0.076)	-0.093	0.206
delta hat	1.473	(0.383)	0.721	2.224	2.238	(0.788)	0.694	3.782				
sigma2 t/sigma2 d	8.775	(2.992)	2.909	14.640	9.279	(3.081)	3.240	15.318				
plive10					-0.135	(0.065)	-0.262	-0.007	-0.016	(0.047)	-0.108	0.076
N inds	14,969				14,718				14,718			
N obs	58,040				55,592				55,592			

Step 3: working decisions

Neural-network figure

Figure: Neural network model. From Wang et al (2019a)



back

Step 3: working decisions

Neural-network approach

- For a binary outcome p,
  - Let V_0 and V_1 denote last layer's units pre-transformation (non-linear functions of the inputs)
  - Transformation at the last layer, $s_j = \frac{e^{V_j}}{e^{V_0}+e^{V_1}}$, $j = 0, 1$
  - Loss function $-\sum_{\text{obs}} \left\{ \mathbb{1}(p = 0) log(s_0) + \mathbb{1}(p = 1) log(s_1) \right\}$

Step 3: working decisions

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Step 3: working decisions

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- Hence, it is a generalization of a logit with non-linear index
- Optimization problem is non-convex and may have multiple local minima
  - Weight regularization, multiple starting values, ensemble of results, search of hyperparameters
- Algorithm uses gradient descent and back propagation to find the weights

back

Step 3: working decisions

NN strategy with unobserved inputs

- In this paper, I apply neural networks to panel data

$$\Leftrightarrow \max \sum_{i,t} log\big(\mathbb{P}(p_{it}|x_{it})\big)$$

Step 3: working decisions

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Step 3: working decisions

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- These latent variables can be subsumed in time-invariant unobserved $(\alpha_i, \hat{\delta}_{i0}) \equiv \eta_i$, with η_i included in x_{it}
- We want

$$\max \sum_{i} log \int \prod_{t} \mathbb{P}(p_{it}|x_{it}) f(\eta_i) d\eta_i$$

back

Step 3: working decisions

NN strategy with unobserved inputs

- Insights from EM-algorithm

$$arg\max_{\theta} \sum_i log \int \mathbb{P}(p_i^T|x_i^T;\theta) f(\eta_i) d\eta_i \Leftrightarrow arg\max_{\theta} \sum_i \int log \mathbb{P}(p_i^T|x_i^T;\theta) \underbrace{f(\eta_i|p_i^T;\theta)}_{\substack{\text{unknown}\\ \text{posterior}}} d\eta_i$$

Step 3: working decisions

NN strategy with unobserved inputs

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- EM-algorithm's iterative strategy: given θ_{k-1}
  1. Fix $f(\eta_i|p_i^T;\theta_{k-1})$
  2. Estimate θ_k using this distribution on the RHS

Step 3: working decisions

NN strategy with unobserved inputs

- Insights from EM-algorithm

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  2. Estimate θ_k using this distribution on the RHS

- In this paper,
  1. Use MCMC to draw η_i from the posterior $f(\eta_i|p_i^T;\theta_{k-1})$
  2. Estimate a neural network in the augmented data

$$\max \sum_i \sum_{\text{draws}} \sum_t log \mathbb{P}(p_{it}|x_{it})$$

back

Step 3: working decisions

NN strategy with unobserved inputs

- Use this iterative process as a convenient implementation

- Beginning with distribution that already incorporates health history and history of survival expectations

$$\mathbb{P}(\eta_i | h_{i0}, \ldots h_{iT}, plive10_{i1}, \ldots plive10_{iT})$$

where $\eta_i = (\alpha_i, \hat{\delta}_{i0})$

back

Step 3: working decisions

NN results

Table: Loss and accuracy across 100 trainings

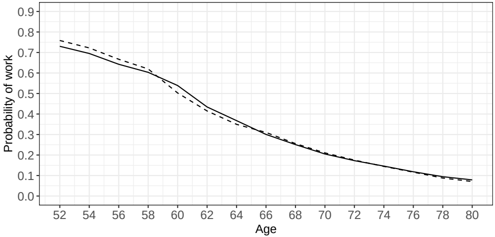
	Mean	Median	SD
Loss	0.313	0.312	0.003
Accuracy	0.883	0.883	0.0005

back

Step 3: working decisions

NN results

Figure: Overall fit

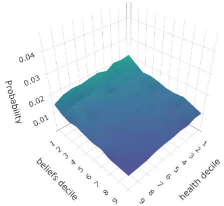


Sample of individuals who in their lifetime have worked at least 20 years. 12,493 individuals with 47,670 correlative observations.

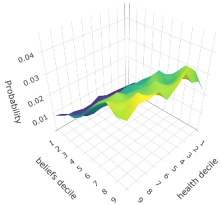
back

Step 3: working decisions

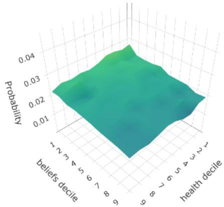
NN results: average marginal effects of beliefs $\hat{\delta}_{it-1}$ on labor participation p_{it} back



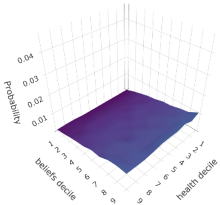
(a) $p_{it-1} = 1$ and $age_{it} \in [52, 59]$



(b) $p_{it-1} = 0$ and $age_{it} \in [52, 59]$



(c) $p_{it-1} = 1$ and $age_{it} \in [66, 75]$

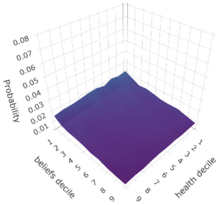


(d) $p_{it-1} = 0$ and $age_{it} \in [66, 75]$

Step 3: working decisions

NN results: average marginal effects of health h_{it-1} on labor participation p_{it}

back



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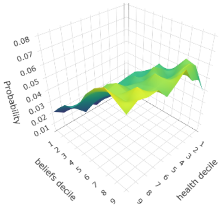

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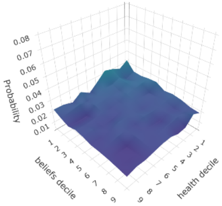

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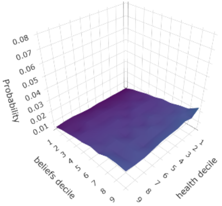

(d) $p_{it-1} = 0$ and $age_{it} \in [66, 75]$

Step 3: working decisions

Result: Eliminating bias in beliefs would **increase** probability of work

(2) Effect of eliminating initial negative bias b on $\mathbb{P}(p_{it} = 1 | \Omega_{it-1})$

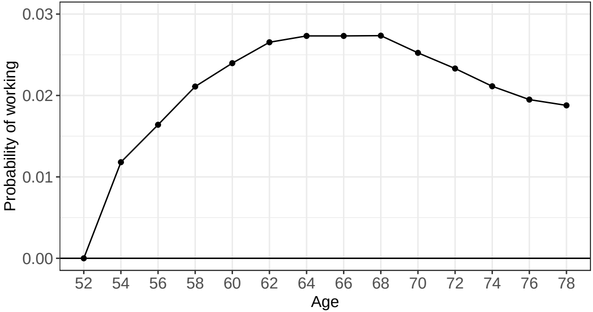

Figure: Impulse response function to eliminate initial bias b

per individual

back

Step 3: working decisions

NN impulse response functions to a reduction in bias $\hat{\delta}_{it} - \delta_i$

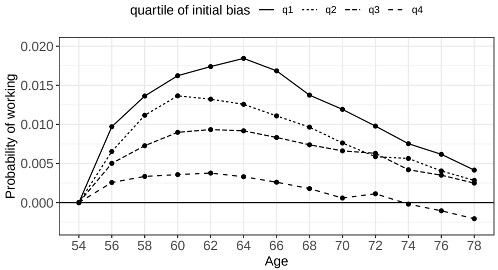

Figure: Bias reduced in half, by quartile of bias

At 54, p_{it} has mean 0.73 and sd 0.44
At 66, p_{it} has mean 0.34 and sd 0.47
At 78, p_{it} has mean 0.11 and sd 0.31

Bias at 54 goes between -0.16 to 0.12, with a mean and median of -0.059 back

Step 3: working decisions

Result: Marginal changes in health have **small** effects on working decisions through information

(3) Decomposition of effect health shock ϵ_{it-1} on $\mathbb{P}(p_{it} = 1|\Omega_{it-1})$

$$\frac{d\mathbb{P}(p_{it}=1)}{d\epsilon_{it-1}} = \underbrace{\frac{\partial \mathbb{P}(p_{it}=1)}{\partial h_{it-1}}}_{\text{persistence effect}} + \underbrace{\frac{\partial \mathbb{P}(p_{it}=1)}{\partial \hat{\delta}_{it-1}} \overbrace{\frac{(t-1)\hat{\sigma}^2_{it-1}}{\sigma^2_\epsilon}}^{\text{factor}}}_{\text{information effect}}$$

- If $\rho = 0$, persistence effect is zero
- If $\lambda = 0$, information effect is zero
- Results show the persistence effect dominates (avg over 98%)
- Why? Changes in health translates into small changes in beliefs

Decomposition back

Step 3: working decisions

Decomposition of the effect of a health shock ϵ_{it-1} in p_{it}

back

Table: Avg mg effects of health h_{it-1} and beliefs $\hat{\delta}_{it-1}$ on $\mathbb{P}(p_{it} = 1)$

		$p_{it-1} = 0$		$p_{it-1} = 1$	
age	factor	Avg mg effects of h_{it-1}	Avg mg effects of $\hat{\delta}_{it-1}$	Avg mg effects of h_{it-1}	Avg mg effects of $\hat{\delta}_{it-1}$
52	0.003	0.056	0.028	0.010	0.011
54	0.006	0.049	0.024	0.011	0.012
56	0.009	0.043	0.021	0.013	0.013
58	0.011	0.038	0.018	0.015	0.015
60	0.013	0.033	0.016	0.017	0.017
62	0.014	0.028	0.013	0.018	0.018
64	0.015	0.022	0.010	0.020	0.020
66	0.015	0.019	0.009	0.021	0.021
68	0.014	0.015	0.007	0.021	0.021
70	0.014	0.013	0.006	0.021	0.022
72	0.013	0.010	0.004	0.022	0.022
74	0.012	0.008	0.003	0.022	0.022

Step 4: information experiment

Biomarkers as signals of δ_i

- So far, results show
  - Beliefs matter for working decisions

Step 4: information experiment

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- Can we provide information to correct beliefs? And affect working decisions?

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  - Some results are informed back: blood glucose, HDL and total cholesterol
    These results provide *information about health*

Step 4: information experiment

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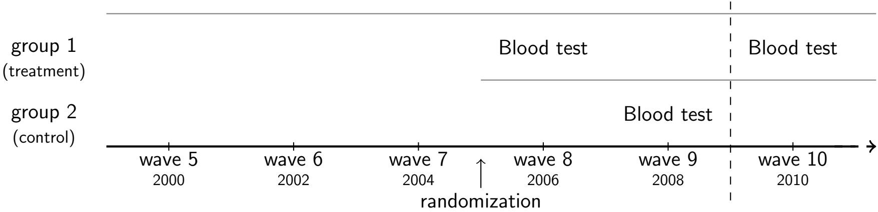
- Blood-based biomarkers introduced in 2006
  - Some results are informed back: blood glucose, HDL and total cholesterol
    These results provide *information about health*
  - Info collected and provided to a random half of the sample, every other wave
    Hence, we have *exogenous source of variation*

Lab results

Step 4: information experiment

Collection of biomarkers

Figure: Timing of the biomarker collection and information experiment



Step 4: information experiment

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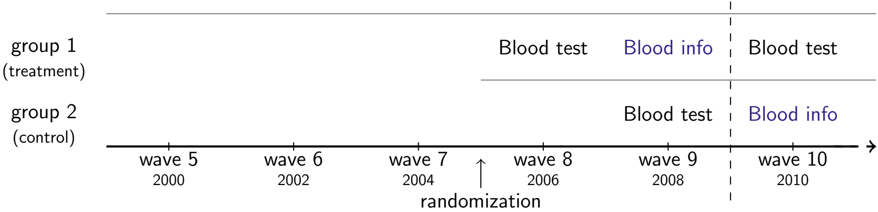

Step 4: information experiment

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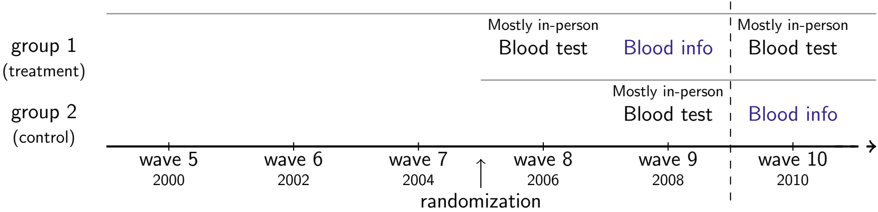

Step 4: information experiment

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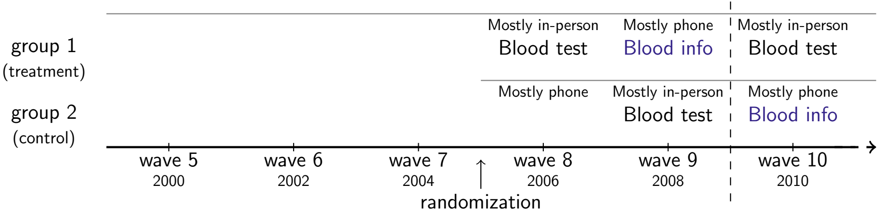

Step 4: information experiment

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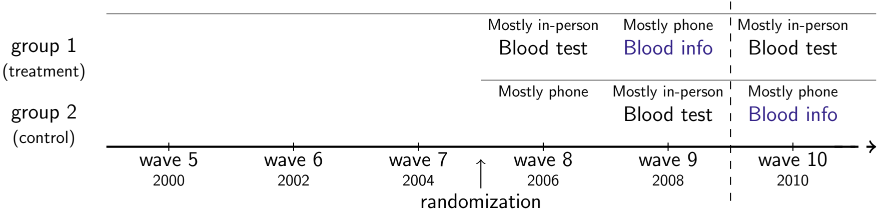

- DD waves 7 and 8: mode collection effects (in-person)

Step 4: information experiment

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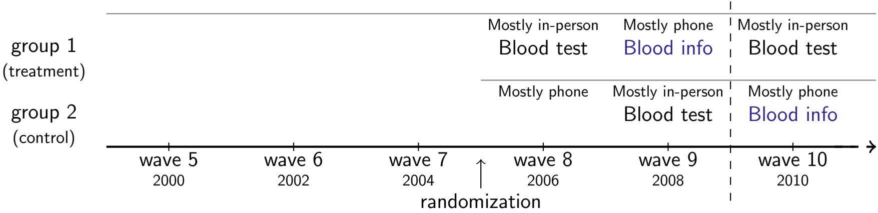

- DD waves 7 and 8: mode collection effects (in-person)
- DD waves 7 and 9: information effect - mode collection effects (in-person)

Step 4: information experiment

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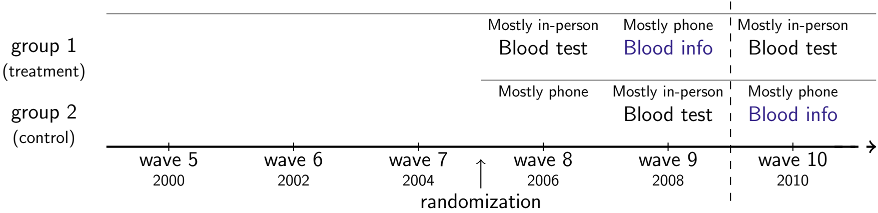

- DD waves 7 and 8: mode collection effects (in-person)
- DD waves 7 and 9: information effect - mode collection effects (in-person)
- Two variables:
  - Survival expectations $plive10$ i.e. effects on beliefs
  - Working decision p i.e. effects on outcomes

Step 4: information experiment

Biomarker results from a data perspective

- Overall results
  - Survival expectations $plive10$: 1.36 pp not significant
  - Working decision p: 0.02 pp not significant

Step 4: information experiment

Biomarker results from a data perspective

- Overall results
  - Survival expectations $plive10$: 1.36 pp not significant
  - Working decision p: 0.02 pp not significant
- Larger effects for college graduates
  - Survival expectations $plive10$: 5.12 pp significant at 5%
  - Working decision p: 0.04 pp not significant

DD results DD bad results back

Step 4: information experiment

Biomarker results from a model perspective

- Let l_{it} be blood-glucose information

- In 2008, treatment group has two available signals of δ_i

$$\begin{aligned} h_{it} &= \rho h_{it-1} + \alpha_i + \delta_i \cdot t + \epsilon_{it} \\ l_{it} &= \tau_0 + \tau_1 h_{it-1} + \tau_2 \alpha_i + \tau_3 \delta_i \cdot t + \tau_4 \cdot t + \tau_5 \cdot x_i + \omega_{it}, \end{aligned}$$

Step 4: information experiment

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- For them, beliefs $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ is a function of $\tau_0, \ldots \tau_5, \sigma_\omega$ too

Step 4: information experiment

Biomarker results from a model perspective

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$$
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\end{aligned}
$$

- For them, beliefs $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ is a function of $\tau_0, \ldots \tau_5, \sigma_\omega$ too

- Use future waves of control group for estimating these parameters

Step 4: information experiment

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\end{aligned}
$$

- For them, beliefs $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ is a function of $\tau_0, \ldots \tau_5, \sigma_\omega$ too

- Use future waves of control group for estimating these parameters

- Use those values to predict $(\hat{\delta}_{it}, \hat{\sigma}_t^2)$ and $plive10_{it}$ for treatment group

Step 4: information experiment

Biomarker results from a model perspective

- Results
  - Survival expectations $plive10_{it}$ increase by 0.4 pp only

- These model-based results are consistent with the data results

- They provide an interpretation: magnitude of the signal is too small

model-based results back

Step 4: information experiment

MLE of the health process including lab results as explanatory variable

back

	Coefficient	Pvalue
ρ	0.189	0.000
γ	0.002	0.057
σ_ϵ	0.264	0.000
μ_α	4.450	0.000
$\tau_{\alpha Total\_chol}$	0.170	0.000
$\tau_{\alpha HDL}$	-0.030	0.467
$\tau_{\alpha HBP}$	-0.161	0.001
μ_δ	-0.053	0.000
$\tau_{\delta Total\_chol}$	-0.005	0.396
$\tau_{\delta HDL}$	-0.010	0.076
$\tau_{\delta HBP}$	-0.028	0.000
σ_α	0.442	0.000
σ_δ	0.040	0.000
ϕ	-0.057	0.336
...	...	
N observations	7,768	
N individuals	1,344	
-LL	4,223.2	

The lab results variables are dummies indicating values outside the normal ranges.

Step 4: information experiment

DD results

		Survival expectations ($plive10_{iw}$)			Work choice (p_{iw})		
		All	Less college	College	All	Less college	College
group 1	d_{g_i}	-0.47	-0.24	-1.38	0.00	0.01	-0.01
wave 6	d_{w6}	-1.42***	-1.21**	-2.09**	-0.07***	-0.07***	-0.09***
wave 7	d_{w7}	-1.50***	-1.44***	-1.72**	-0.12***	-0.12***	-0.12***
wave 8	d_{w8}	-6.41***	-6.12***	-7.37***	-0.16***	-0.16***	-0.19***
wave 9	d_{w9}	-3.57***	-3.22***	-4.70***	-0.20***	-0.20***	-0.22***
group 1, wave 6	$d_{g_i} \cdot d_{w6}$	0.28	-0.06	1.37	0.01	0.00	0.02
group 1, wave 7	$d_{g_i} \cdot d_{w7}$	-0.27	-0.24	-0.33	0.01	0.01	0.01
group 1, wave 8	$d_{g_i} \cdot d_{w8}$ (a)	1.77**	1.29	3.31***	0.01	0.00	0.03
group 1, wave 9	$d_{g_i} \cdot d_{w9}$ (b)	-0.42	-1.12	1.82	0.01	0.01	0.00
Constant		53.97***	52.42***	58.96***	0.49***	0.45***	0.61***
Observations		41,930	31,815	10,115	41,923	31,810	10,113
R-squared		0.004	0.004	0.005	0.021	0.021	0.022
Interview mode effect (a)		1.77**	1.29	3.31**	0.01	0.00	0.03
Information effect (a)+(b)		1.36	1.65	5.12**	0.02	0.01	0.04

$$y_{iw} = \beta_0 + \beta_1 d_{g_i} + \beta_{2w} d_w + \beta_{3w} d_{g_i} \cdot d_w + \epsilon_{iw}$$

back

Step 4: biomarkers as signals of δ_i

Reduced-form results distinguishing bad vs good test results

back

		Survival expectations $plive10_{iw}$	Working decisions p_{iw}
group 1	d_{g_i}	-0.39	-0.01
group 1, bad results	d_{b_i}	-0.37	0.04**
wave 6	d_{w6}	-1.42***	-0.07***
wave 7	d_{w7}	-1.50***	-0.12***
wave 8	d_{w8}	-6.41***	-0.16***
wave 9	d_{w9}	-3.57***	-0.20***
group 1, wave 6	$d_{g_i} \cdot d_{w6}$	0.58	0.01
group 1, wave 7	$d_{g_i} \cdot d_{w7}$	0.15	0.02*
group 1, wave 8	$d_{g_i} \cdot d_{w8}$	2.23***	0.02*
group 1, wave 9	$d_{g_i} \cdot d_{w9}$	-0.05	0.02
group 1, bad results, wave 6	$d_{g_i} \cdot d_{b_i} \cdot d_{w6}$	-1.25	-0.01
group 1, bad results, wave 7	$d_{g_i} \cdot d_{b_i} \cdot d_{w7}$	-1.75*	-0.04**
group 1, bad results, wave 8	$d_{g_i} \cdot d_{b_i} \cdot d_{w8}$	-1.94*	-0.05***
group 1, bad results, wave 9	$d_{g_i} \cdot d_{b_i} \cdot d_{w9}$	-1.56	-0.03
Constant		53.97***	0.49***
Observations		41,930	41,923
% of group 1 individuals with bad results		12.29	12.30

Step 4: biomarkers as signals of δ_i

Model-based results

Table: Predicted $plive10$ with health and blood glucose as signals

	Number of observations	Predicted survival expectations		
		wave 8	wave 9	wave 9 - wave 8
Control (group 2)	4,852	45.8	45.4	-0.3
Treated (group 1)	5,357	44.8	44.9	0.1
Treated with bad blood glucose result	552	39.1	38.5	-0.5
Treated with good blood glucose result	3,649	46.0	46.3	0.3
Treated no blood glucose result	1,156	43.8	43.7	-0.2

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