Healthy Habits and Inequality

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Preliminary

Introduction

- Large body of research documenting economic inequality
  (*wealth, consumption, income, wages*)
- Growing interest in inequality in health outcomes and on how it relates to economic inequality
- We aim to explore the connection between health and economic inequality by investigating:
  1. Impact of different lifestyles on health dynamics, economic outcomes, welfare
  2. The determinants of different lifestyles

Main ideas

- We conjecture that heterogeneity in lifestyle is an important driver of health inequality and of its correlation with economic inequality
  - High SES tend to adopt healthier habits
    Hiscock *et al* (2012); McLaren (2007)
  - Smoking, regular exercise, or healthy diet linked to better health outcomes
    Zaninotto, Head, Steptoe (2020); Li *et al* (2018)
  - Large welfare and economic cost of bad health.
    De Nardi, Pashchenko, Porapakkarm (2022); Kopecky, Hosseini, Zhao (2022)

- We seek to
  - Measure lifestyles and quantify their effects on health dynamics
  - Connect health and economic inequality
  - Understand the determinants of different lifestyles
  - Quantify the economic and welfare costs of unhealthy lifestyles (not there yet)

What we do

1. Data

- We identify patterns in health behavior (preventive tests, substance abuse, obesity) driving health dynamics in both HRS and PSID
- We find that
  - Health behavior is well represented by three healthy habits types: protective, detrimental, and harmful
  - Large LE_{50} gradient: 9 years between protective and harmful
  - Healthy habits are correlated w/ education but carry independent information
    - Healthy habit gradient of similar size within education groups
    - Harmful types much more frequent among the less educated
    - Healthy habits explain 40% of the education gradient in LE_{50}

What we do

2. Model

- We build a life-cycle heterogeneous agents model with idiosyncratic labor market and health risks
  - Individuals differ in health habits and education as well as wealth and health
  - Health dynamics driven by previous estimates
  - Education and healthy habit choices taken together early in life
- Estimate the model
  → Understand sources of heterogeneity across individuals
- Counterfactuals
  → Understand role of healthy habits on economic inequality
  → Understand determinants of healthy habits

The Data

- The HRS and PSID provide an unbalanced panel of individuals $i = 1, ..., N$ followed for $t = 1, ..., T$ periods
- Standard demographic information: gender (g), education (e), age (a_t)
- Wide array of information on health status and health behavior
  - Health state (h_t): self-reported health (good/bad) + death
  - Health behavior (z_{mt}):
    1. Preventive cancer tests (mammography / prostate check)
    2. Cholesterol test
    3. Flu shot
    4. Heavy drinking (2+ drinks on the day they drink)
    5. Smoking
    6. Obesity

Latent types

- We assume that observed health behavior (z_{mt}) is the result of some unobserved time-invariant latent factor (y)
  - The latent factor is represented by a few discrete groups $y \in \{y_1, y_2, ...\}$.
- We interpret the latent factor (y) as the lifestyle / healthy habit type
- We propose an econometric model exploiting both the cross-sectional and the time-series dimension of our data to
  - Allocate individuals to healthy habit types
  - Measure the importance of healthy habit types on health dynamics

Econometric Model

Overview

- We *jointly estimate* health dynamics and healthy habits types using a mixture model:

$$p(\boldsymbol{z}, \boldsymbol{h}|c, s, e, a, h_0) = \sum_{y \in Y} p(\boldsymbol{z}, \boldsymbol{h}|c, s, e, a, h_0, y) p(y|c, s, e, a, h_0)$$
$$= \sum_{y \in Y} p(\boldsymbol{z}|\boldsymbol{h}, a, h_0, y) p(\boldsymbol{h}|s, e, a, h_0, y) p(y|c, s, e, a, h_0)$$

  - By estimating types and transition jointly, we find the types that better represent both the observed behaviour and the health transitions (vs. k-means clustering on habits and then transitions)

- Conditional on the health habit type (y)
  - Health behaviours (z_{mt}) are iid, modelled through a probit
  - Health outcomes (h_t) are markovian, modelled through a nested probit

Econometric Model

1. Healthy Habits

- We model the probability of individual i of reporting the m'th behaviour $(z_{mt} = 1)$ at time t as a probit model.
  - There is a latent variable (z^*_{mt}) that depends on type (y), age (a_t), health (h_t), and an idiosyncratic shock (ϵ_t)

$$z^*_{mt} = \gamma_{0,m,y} + \gamma_{1,m,y} a_t + \gamma_{2,m,y} a_t^2 + \gamma_{3,m,y} h_t + \epsilon_t, \quad \epsilon_t \sim N(0,1)$$

  - Then,

$$\text{Prob}\left(z_{mt} = 1\right) = \text{Prob}\left(z^*_{mt} > 0\right) = \underbrace{\alpha_m(y, a_t, h_t)}_{\alpha_{mt}}$$

  - Considering independence of health behaviour given type, the probability of observing a sequence of health behaviours $\boldsymbol{z}$ for an individual across time, is assumed to be given by:

$$p(\boldsymbol{z}|\boldsymbol{h}, y) = \prod_{t=1}^{T} \prod_{m=1}^{M} \alpha_{mt}^{z_{mt}} \left(1 - \alpha_{mt}\right)^{1-z_{mt}}$$

Econometric Model

2. Health Dynamics

- We model the probability of reporting some health $h' \in \{Good, Bad, Dead\}$ next period as a nested probit model
  1. First nest: Alive/Dead
  2. Second nest: Good/Bad cond on survival

  – There are latent variables ($h^*_{h,h'}$) that depend on gender (g), education (e), type (y), health (h), age (a), and an idiosyncratic shock ($\epsilon_{h'}$)

$$h^*_{h,h'} = f(a, s, e, y; \boldsymbol{\beta}_{h,h'}) + \epsilon_{h'}$$

with,

$$f(a, g, e, y; \boldsymbol{\beta}_{h'}) = \beta_{0,y,e,g,h,h'} + \beta_{1,y,e,g,h,h'} a$$

  – Then,

$$\text{Prob}\left(h' = Dead\right) = \text{Prob}\left(h^*_{h,h'=Dead} > 0\right)$$
$$\text{Prob}\left(h' = Good | Survival\right) = \text{Prob}\left(h^*_{h,h'=Good} > 0 \,|\, Survival\right)$$

Econometric Model

3. Weights

- The mixture weights at the initial age (age 25 are modeled as a multinomial probit model:

$$
\begin{aligned}
y_1^* =& \lambda_{0,s,e,c}^1 + \lambda_{1,s,e}^1 h + \epsilon_1 \\
&\vdots \\
y_Y^* =& \lambda_{0,s,e,c}^Y + \lambda_{1,s,e}^Y h + \epsilon_Y ,
\end{aligned}
$$

- We compute weights for future ages using the health transition model:

$$
p(y, h_t | s, e, c) = \sum_{h_{t-1}} p(h_t | h_{t-1}, y, s, e, c) p(y, h_{t-1} | s, e, c)
$$

Results: Healthy Habits

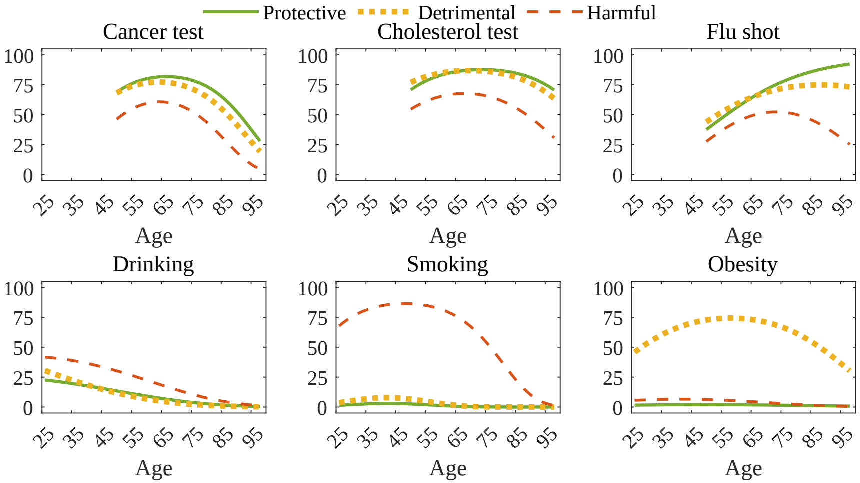


Figure 1: Probability of having a health habit by health behavior type as individuals age

Results: Mixture Weights

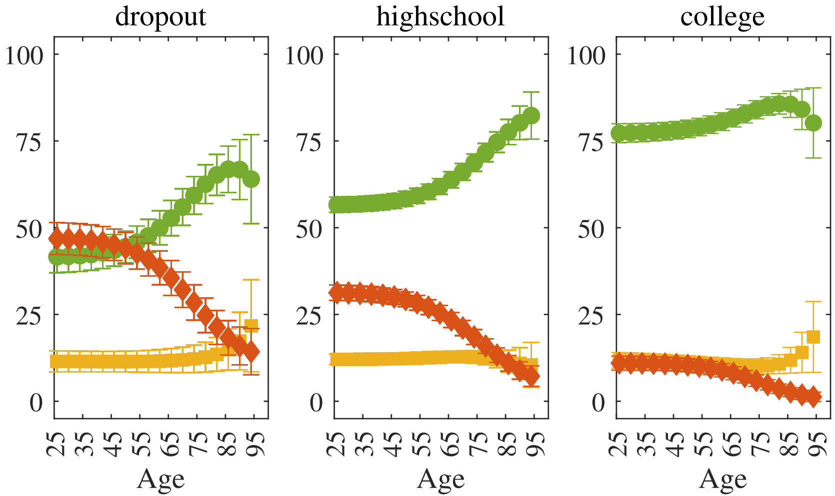


Figure 2: Probability of health behavior type as individuals age. Males.

Results: Health Dynamics

Males

Table 1: Expected duration of each health state at age 50 across behavior types

Health Behavior	Fraction	Life Expectancy	=	Good Health	+	Bad Health
			Dropouts			
Protective	43.7	27.9		17.3		10.6
Detrimental	11.2	24.8		12.3		12.5
Harmful	45.1	19.3		10.7		8.6
Average	-	23.7		14.3		11.2
			High-school			
Protective	57.9	29.5		23.9		5.6
Detrimental	12.4	27.3		18.4		8.9
Harmful	29.7	20.9		14.8		6.1
Average	-	26.7		21.2		6.6
			College			
Protective	78.3	32.9		29.7		3.2
Detrimental	11.2	29.8		22.4		7.4
Harmful	10.5	22.5		17.9		4.6
Average	-	31.5		27.6		3.8

Results: Health Dynamics

Females

Table 2: Expected duration of each health state at age 50 across behavior types

Health Behavior	Fraction	Life Expectancy	=	Good Health	+	Bad Health
			Women: Dropouts			
Protective	43.0	29.4		15.9		13.6
Detrimental	27.1	27.1		9.9		17.2
Harmful	29.9	20.5		8.8		11.7
Average	-	26.1		12.2		14.1
			Women: High-school			
Protective	56.7	32.9		26.9		6.1
Detrimental	21.6	29.3		18.7		10.6
Harmful	21.8	24.2		16.5		7.7
Average	-	30.2		22.9		7.4
			Women: College			
Protective	73.9	34.8		31.0		3.8
Detrimental	17.0	30.1		23.7		6.4
Harmful	9.2	26.7		20.0		6.7
Average	-	33.3		28.4		4.5

Results: Health Dynamics

- More educated individuals tend to adopt healthier habits.
  - The probability that a college male has a harmful health behavior is 4.3 times smaller than a dropout.
- If dropout males had the same proportion of health behavior types than college males, their life expectancy would increase by 3 extra years.
  - This corresponds to 40% of the observed difference in life-expectancy at age 50 between college graduates males and high-school dropouts males.
- If dropout females had the same proportion of health behavior types than college females, their life expectancy would increase by 2.1 extra years.
  - This corresponds to 30% of the observed difference in life-expectancy at age 50 between college graduates females and high-school dropouts females.

Results: Cohorts

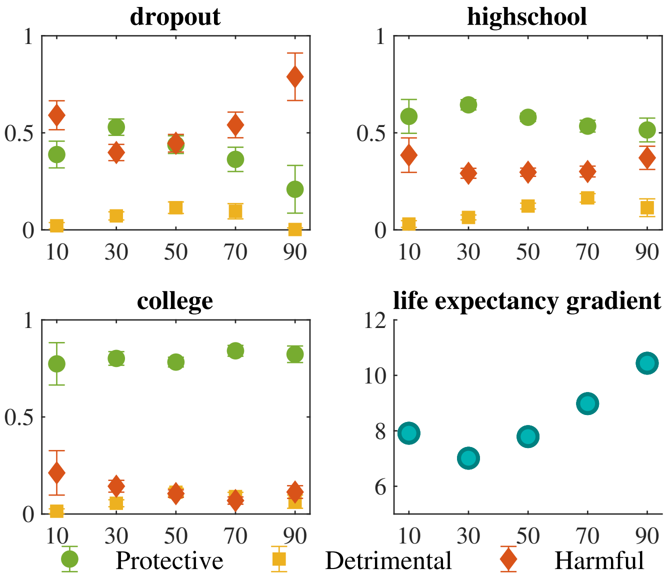


Figure 3: Probability of health behavior type at age 50 across cohorts. Males.

The Model

Three different stages

1. Early life
   - Choice of education and lifestyle
2. Working Age
   - Standard life-cycle incomplete-markets model of consumption with health and labor market risks

     De Nardi, Pashchenko, Porapakkarm (2022)
   - A model period is two years, individuals retire at age R
3. Retirement
   - As above, but without labor market risks

Working Age (stage 2)

State variables

- Working agents are heterogeneous with respect to:
  - education (e)
  - health behavior (y)
  - health status (h_t)
  - persistent shock to earnings (ξ_t)
  - persistent shock to medical expenses (ζ_t)
  - cash-on-hand (x_t)

Working Age (stage 2)

Worker's problem

- Worker's problem can be written as:

$$V_t^{e,y}(x,h,\xi,\zeta) = \max_{c,k'} \Big\{ u(c,h) + \beta s_t^{e,y}(h) \sum_{h'} \Gamma_t^{e,y}(h) \, \mathbb{E}_{\xi,\zeta,\epsilon} \left[V_{t+1}^{e,y}(x',h',\xi',\zeta') \right] + \beta \left(1 - s_t^{e,y}(h)\right) v(k') \Big\}$$

s.t.

$$\begin{aligned} k' &= x - c \\ x' &= \min\{(1+r)\,k' + w_t^{e,y}(\zeta',h',\epsilon') - m_t(\xi',h') - Tax, \underline{c}\} \\ Tax &= T(w_t^{e,y}(\zeta',h',\epsilon')) + \tau_{MCR} w_t^{e,y}(\zeta',h',\epsilon') + \tau_{ss} \min\{w^{e,y}(\zeta',h',\epsilon'), w_{ss}\} \end{aligned}$$

Flow utility: $u(c,h) = (1-\delta_{bh}) \dfrac{c^{1-\sigma}}{1-\sigma} + b$

Bequest motive: $v(a) = \theta \dfrac{(a+\underline{k})^{1-\sigma}}{1-\sigma}$

Model Estimation (stage 2 & 3)

A two-step estimation strategy

1. We set parameters related to demographics, taxes, social security benefits, and estimate the shock processes directly from the data.

2. Method of Simulated Moments to estimate our remaining model parameters
   - We match p25, p50, p75 wealth moments across age, education and health behavior types.
   - We minimize the sum square of the difference between the targeted and simulated wealth moments.

Model Estimation (stage 2 & 3)

Internally estimated parameters

Parameter	Description	Value
β	discount factor	0.932
$\underline{c}$	consumption floor	3.93
δ_{bh}	disutility from bad health	0.278
$\underline{k}$	bequest motive: non-homoteticity	45.5
θ	bequest motive: marginal utility	0.107
b	value of life	1.33

Model Estimation (stage 2 & 3)

Model Fit

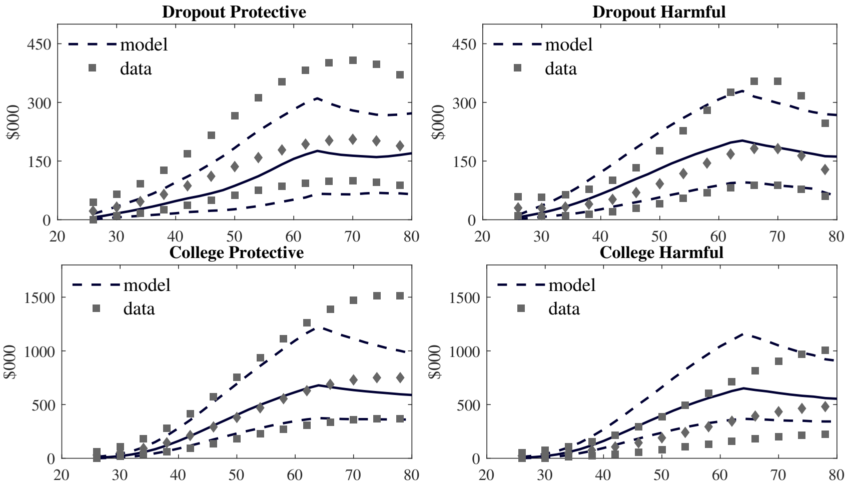


Figure 4: Wealth distribution: model vs data

Model Fit

Stage 2 & 3

- Good fit for the differences in wealth accumulation profiles across education categories
- Not so good fit for the differences in wealth accumulation across health behavior types
  - Differences in βs across health behaviour types?

Early life (stage 1)

- Let $V_0^{e,y}$ be the value of starting working life with type (e, y)
  (coming from Stage 2)

- Let $c_{e,y}$ be the average cost of undertaking choice (e, y)
  (we normalize $c_{\tilde{e},\tilde{y}} = 0$)

- Let $\epsilon_{e,y}$ be the idiosyncratic cost of undertaking choice (e, y)

→ Teenagers/parents make once-and-for-all choices of (e, y):

$$\max_{e,y} \left\{ V_0^{e,y} - c_{e,y} - \sigma \epsilon_{e,y} \right\}$$

Early life (stage 1)

- With extreme value distributed shocks, the fraction of individuals taking each choice is,

$$q_{e,y} = \frac{exp\left[(V_0^{e,y} - c_{e,y})/\sigma\right]}{\sum_{e_i,y_j} exp\left[(V_0^{e_i,y_j} - c_{e_i,y_j})/\sigma\right]}$$

- One can write

$$\log q_{e,y} - \log q_{\tilde{e},\tilde{y}} = \frac{1}{\sigma}\left(V_0^{e,y} - V_0^{\tilde{e},\tilde{y}}\right) - \frac{1}{\sigma} c_{e,y}$$

- Use this equation to:
  - Estimate σ by OLS (covariance between differences in type frequencies)
  - Recover investment costs from regression residuals

Early life (stage 1)

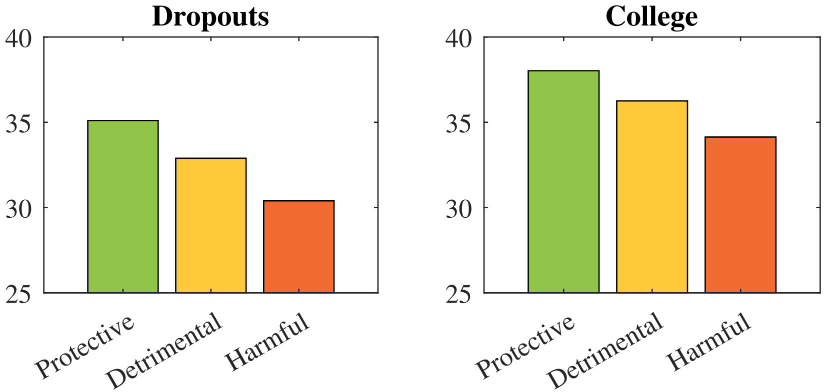
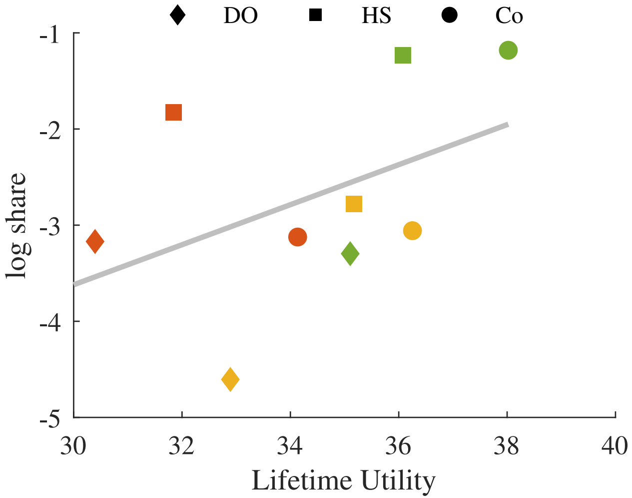


Figure 5: Lifetime utility at age 23: $V_0^{e,y}$

- Dropouts: Harmful: 47%; Protective: 42%
- College: Harmful: 10%; Protective: 77%

Early life (stage 1)



Early life (stage 1)

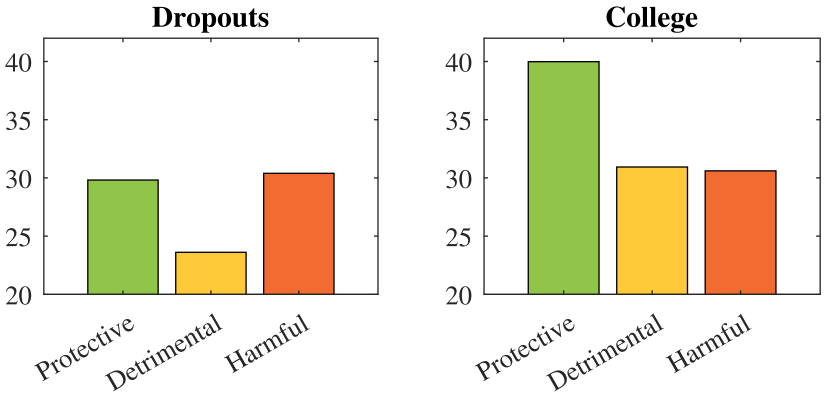


Figure 6: Lifetime utility at age 23: $V_0^{e,y}$ upper panel; $V_0^{e,y} - c_{e,y}$ lower panel

Results

- Differences in lifetime utility at age 23 are unable to explain why dropouts don't adopt healthier habits as dropouts would benefit more than college graduates from doing so.
- In order to match the large share of harmful-dropout and protective-college types negative costs are needed.
  - For a dropout it is more costly to adopt a protective than a harmful behavior
  - For a college, the reverse is true.
- This suggests that there are complementarities in education and health behavior choices beyond the ones incorporated in the model that drive the large health inequalities observed in the data

Counterfactuals

- We ran two counterfactuals to quantify the effect of nature versus nurture in the decision of types at young ages:

1. Choices taken based exclusively on $V^{e,y}$ at the initial age: $c_{e,y} = \bar{c}\ \forall\ e, y$
2. Revenue-neutral tax reform of labor earning taxes: the US becomes Denmark (top decile marginal tax rate $38\% \rightarrow 55\%$)

	College (%)	Protective (%)	LE$_{50}$ (yr)	LE$_{50}$ gradient (yr)	$\bar{V}$	$var(V)$
Benchmark	40	63	26.3	7.9	35.6	5.5
No costs	45	47	26.0	5.0	35.4	4.1
$US \rightarrow DNK$	38	62	26.2	8.0	35.8	5.1

Counterfactuals

- Unobserved initial factors (parental investment, peers, genes) are key drivers of the observed health and welfare inequality.
  - Without costs, the gradient in LE would decrease in 3.5 years or 45%
  - Dropouts behave better: fraction of harmful $47.5\% \rightarrow 22\%$
  - College behave worse: fraction of harmful $11\% \rightarrow 24\%$
- Increasing the progressivity of the tax system decreases the variance in welfare inequality but deteriorates health inequalities.
  - The economic incentive of well behaving for the dropouts decreases.