Mental health and lifecycle inequality

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Roadmap

Questions and spoilers

How much does mental health (MH) inequality matter for lifetime earnings inequality?

- Estimate a life-cycle model of consumption, labor, wealth with heterogeneous MH
- Run counterfactuals with no MH inequality, compare earnings inequality

Eventually: how much does lifetime earnings inequality matter for mental health inequality?

- Run counterfactuals with no lifetime earnings/labor inequality, compare mental health inequality

Today...

- Stuff

Labor earnings

- something about how earnings = emp*hours*wage

Motivation

- Why Mental Health (MH)?
  - Prevalent and costly (Direct costs, Indirect costs)
    - 1 in 5 adults in US experience mental illness each year (NSDUH) (NIMH)
    - Surgeon general " youth mental health crisis"
  - Policy makers care but difficult to evaluate (WHO, 2023), (OECD)
    - Health care parity mandates affect mental health and welfare?
- Why MH and Labor?
  - Mental health care policy evaluation
  - Large (physical) health and labor outcomes literature

Some Literature

- Physical Health & Labor: Empirical
  - Health effects labor, justify single index: (Bound et al., 1999),(Blundell et al., 2023)
  - Labor effects health (risky behavior & MH) (Schaller and Stevens, 2015)
- Health & the Lifecycle
  - Abramson et al. (2024), Cronin et al. (2023),Jolivet and Postel-Vinay (2020)
  - Borella et al. (2024), (Dal Bianco and Moro, 2022), De Nardi et al. (2021), Hosseini et al. (2021)
- Mental Health & Labor (Econ)
  - MH on employment, maybe wages in NLSY79: (Germinario et al., 2022)
  - Career Effects of Mental Health (Biasi et al., 2021)
  - Retirement effects mental health (Spearing, 2023)

Roadmap

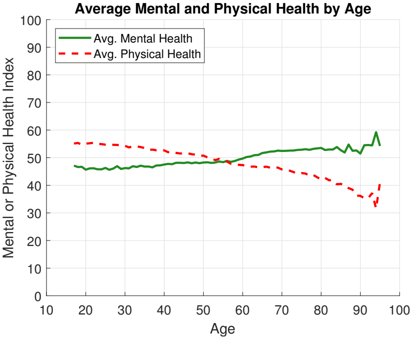
SF12 and UKHLS

Table 12: SF-12 Questionnaire

1	How is your health in general?	7	Did your mental health mean you work less carefully?
2	Does your health limit moderate activities?	8	Did the pain interfere with your work?
3	Does your health limit walking up flights of stairs?	9	Did you feel calm and peaceful?
4	Did your physical health limit the amount of work you do?	10	Did you have a lot of energy?
5	Did your physical health limit the kind of work you do?	11	Did you feel downhearted and depressed?
6	Did your mental health mean you accomplish less?	12	Did you health interfere with your social life?

- UKHLS: Nationally representative survey with income, employment, hours worked, demographics etc.
- SF-12 constructs mental health and physical health indices using principal component analysis
  - shown to be predictive of diagnosis and other health outcomes: Yu et al. (2015),Ohrnberger et al. (2020), Soh et al. (2021).
- Sample is individuals older than 25 in the UK between 2009 and 2020

Average Health Over the Lifecycle



- Index is standardized to a 50 pt. mean and 10 pt. standard deviation
- Average mental health increases by about 1 standard deviation, while average physical health decreases by about 1.5-2 standard deviations over the lifecycle

MH affects labor outcomes

Table 1: Mental and Physical Health Quintile Effects and Labor Outcomes

	Year FE				Individ and Year FE			
	Employment	ln(Earnings)	ln(Wage)	ln(Hours)	Employment	ln(Earnings)	ln(Wage)	ln(Hours)
Fair Mental Health	0.198***	0.006	0.012	-0.006	0.033***	-0.001	0.013	-0.014
	(0.008)	(0.018)	(0.013)	(0.013)	(0.005)	(0.010)	(0.009)	(0.008)
Good Mental Health	0.269***	0.034	0.032*	0.002	0.046***	-0.003	0.016	-0.018*
	(0.009)	(0.020)	(0.014)	(0.014)	(0.006)	(0.010)	(0.009)	(0.008)
Very Good MH	0.305***	0.087***	0.076***	0.011	0.060***	0.002	0.023*	-0.021*
	(0.010)	(0.022)	(0.016)	(0.015)	(0.007)	(0.012)	(0.010)	(0.009)
Excellent Mental Health	0.320***	0.059***	0.060***	-0.001	0.051***	0.002	0.016	-0.014
	(0.007)	(0.017)	(0.013)	(0.012)	(0.006)	(0.010)	(0.009)	(0.008)
Fair Physical Health	0.243***	0.056**	0.047***	0.010	0.044***	0.014	0.017*	-0.003
	(0.009)	(0.017)	(0.013)	(0.012)	(0.007)	(0.009)	(0.008)	(0.008)
Good Physical Health	0.344***	0.073***	0.064***	0.009	0.062***	0.012	0.022*	-0.010
	(0.011)	(0.017)	(0.013)	(0.013)	(0.008)	(0.010)	(0.009)	(0.008)
Very Good PH	0.351***	0.098***	0.080***	0.018	0.038***	0.017	0.024*	-0.008
	(0.013)	(0.019)	(0.015)	(0.014)	(0.010)	(0.011)	(0.010)	(0.009)
Excellent Physical Health	0.398***	0.166***	0.140***	0.026*	0.060***	-0.001	0.019*	-0.020**
	(0.008)	(0.015)	(0.011)	(0.011)	(0.007)	(0.009)	(0.008)	(0.007)
female	-0.090***	-0.416***	-0.150***	-0.266***	0.002	0.210*	0.107*	0.104
	(0.002)	(0.004)	(0.003)	(0.002)	(0.050)	(0.082)	(0.052)	(0.061)
College	0.070***	0.359***	0.308***	0.051***	0.086***	0.066**	0.021	0.045**
	(0.003)	(0.004)	(0.003)	(0.002)	(0.019)	(0.021)	(0.018)	(0.015)
Observations	142055.000	76858.000	76858.000	76858.000	136652.000	73078.000	73078.000	73078.000
R-Square	0.403	0.320	0.266	0.199	0.810	0.881	0.825	0.790
Adj. R-Square	0.402	0.319	0.265	0.198	0.774	0.857	0.788	0.746

All models control for race, marital status, urban location, and an age cubic.

Define good and bad

- For simplicity and congruence with the literature I assume two health states $H \in \{Bad, Good\}$
- Use regression and Wald tests to inform cutoffs.
- Quantile regressions suggests bottom 40% *Bad*, top 60% *Good*
- Other quantile specifications yield low action relative to the increased complexity
    - Might think there are 3 health states G,A,B

Roadmap

Introduction and motivation

Data and preliminary evidence

Lifecycle model

Mental health process

Model estimation and validation

Counterfactuals

Conclusion

Model in words

- Households (HH) live J periods and derive utility from consumption and leisure
- Continuous choices in labor n (switch to discrete), consumption c, and future assets a'
- Constrained by expendable income and time endowment
- Exogenous wage and health process
- Wage is quadratic in age and linear in health
- Two health states $H \in \{Bad, Good\}$: effects wage w_H and time endowment ϕ_H
- Two permanent types
  - Productivity type γ effects the wage process
  - Health type u_H which effects health transition probabilities

Utility and time endowment

Individuals derive period utility from consumption and leisure

$$u\left(c_j, l_j\right) = \frac{\left(c_j^{\alpha} l_j^{1-\alpha}\right)^{1-\sigma}}{1-\sigma}$$

where the time endowment is s.t.

$$l_j = 1 - \phi_n n_j - \phi_H 1_{H=Bad}$$

ϕ_n the time cost of work > 1 to account for commuting etc, ϕ_H is the time cost of bad health.

Consumption constraints

Choices must be s.t.

$$c + a' = z\left(\gamma, j, H\right) \cdot n + a\left(1 + r\right); \forall j$$

and

$$\ln z\left(\gamma_i, j, H_{ij}\right) = w_{0\gamma_i} + w_1 j + w_2 j^2 + w_H 1_{H_{ij}=Bad}$$

$w_{0\gamma}$ depends on productivity type :γ_i. Standard:
$a_0 = a_{J+1} = 0$ and $a_j > -\kappa, ; c_j, n_j \geq 0; \forall j.$

HH recursive optimization problem

The individual's problem:

$$V_j\left(a, \gamma, H, u_H\right) = \max_{c,n,a'} \left\{u\left(c, 1-\phi_n n - \phi_H\left(1-H\right)\right) \right.$$
$$\left. + \beta\, \mathbb{E}_{H'}\, V_{j+1}\left(a', \gamma, H', u_H\right)\right\}$$

s.t.

$$c + a' = z\left(\gamma, j, H\right) \cdot n + a\left(1+r\right); \forall j$$

and

$$a_0 = a_{J+1} = 0 \text{ and } a_j > -\kappa, \text{ and } c_j, n_j \geq 0; \forall j$$

$$H' \sim \Pi_H$$

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Health states and process

- Individuals are said to be in $H = Bad$ health if they are below the 40th percentile of the mental health index. $H = Good$ otherwise.
- I estimate the transition probabilities as the fraction of individuals that make the relevant transition.
  - E.g. the estimated unconditional probability $\hat{\pi}_{B,G}$ is the fraction of people who transition from bad to good health
- The conditional probabilities are estimated similarly.
  - $\hat{\pi}^{u_H}_{B,G}$ is the fraction of people who are the permanent good heath type who transition from bad to good health.
  - $\hat{\pi}^{u_H,j}_{B,G}$ is the fraction of people of age j who are the permanent good heath type who transition from bad to good health.

Health transitions

Health evolves according to the transition matrix

$$\Pi_H = \begin{bmatrix} \pi_{B,B}, & \pi_{B,G} \\ \pi_{G,B}, & \pi_{G,G} \end{bmatrix} = \begin{bmatrix} 0.67, & 0.33 \\ 0.21, & 0.79 \end{bmatrix}$$

where entry $\pi_{B,G}$ is the probability of transitioning from health state $H = Bad$ to $H = Good$.

Above is unconditional. Can condition on age j and permanent health type. E.g. $u_H \in \{u_{Low}, u_{High}\}$

$$\Pi_H(u_H, j) = \begin{bmatrix} \pi_{B,B}^{u_H,j}, & \pi_{B,G}^{u_H,j} \\ \pi_{G,B}^{u_H,j}, & \pi_{G,G}^{u_H,j} \end{bmatrix}.$$

Unconditional transitions by age

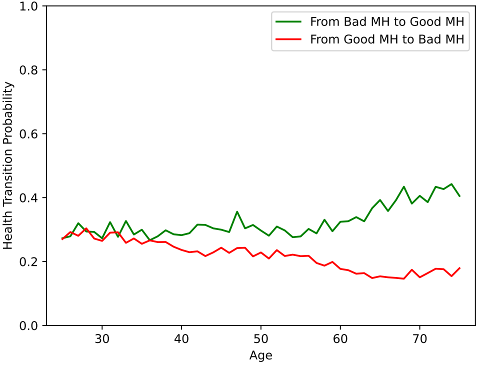


Figure: 1-Year Mental Health Transitions

- health transitions are dynamic over the lifecycle

Simple health types

- For now assume that there are only two health types $u_H \in \{u_{Low}, u_{High}\}$.
- We need to establish a cutoff and partition the individuals.
- Sort mental health observations into above and below the 50th percentile by age
- If an individual is in the bottom half of mental health at his age for most of the observations (greater than 50%) he is the low type
- Otherwise he is the high type

Roadmap

Exogenous parameters

Parameter	Description	Value	Source
R	Gross interest rate	1.02	Benchmark
β	Patience	0.9804	$1/R$
σ	CRRA	0.9999	Benchmark
ϕ_n	Labor time-cost	1.125	Benchmark
ϕ_H	Health time-cost	0.01	Benchmark
$\omega_{H=0}$	Low type pop. weight	0.5699	UKHLS
$\omega_{H=1}$	High type pop. weight	0.4301	$1-\omega_{H=0}$

Table: Exogenous parameters

Calibrated parameters

Parameter	Description	Par. Value	Target Moment	Target Value	Model Value
α	c utility weight	0.3809	Mean hours worked	33.5	33.51
w_1	Linear wage coeff.	0.0266	Wage growth	34.07%	34.14%
w_2	Quad. wage coeff.	-0.0005	Wage decay	30.32%	30.31%
w_H	Health wage coeff.	0.0439	Healthy wage premium	3.53%	3.62%

(a) Calibrated parameters 1

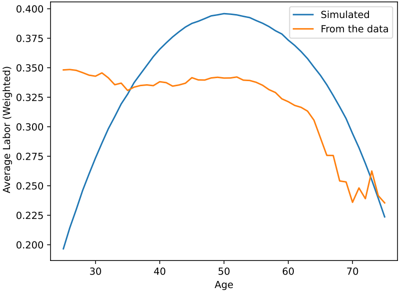
Constant wage coeff.	Ability Level	Value	Weight
$w_{0_{\gamma_1}}$	Low	5	0.28
$w_{0_{\gamma_2}}$	Medium	10	0.59
$w_{0_{\gamma_3}}$	Medium High	15	0.12
$w_{0_{\gamma_4}}$	High	20	0.0
Target Moment	**Target Value**	**Model Value**	
Mean wage, $j = 0$	9.454	9.454	
SD wage, $j = 0$	3.201	3.201	

(b) Calibrated parameters 2

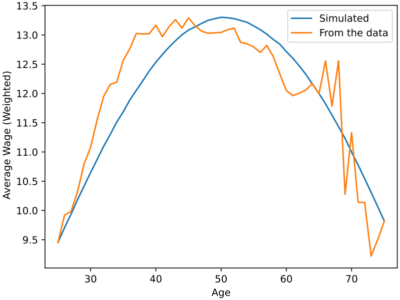
Validation

- Evaluate fit of non targeted moments (especially by health type and by health state)
- Consumption, labor income, wealth/savings, labor participation

Aggregate wage fit



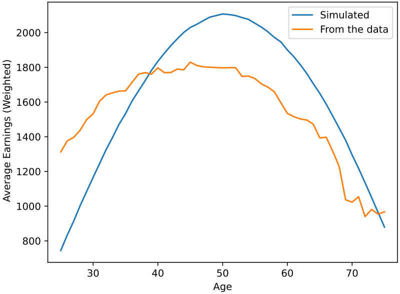
(a) Hours worked (labor)



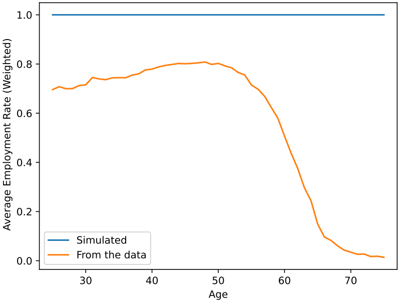
(b) Wage

- Unsurprisingly wage fits well

Aggregate labor earnings and employment



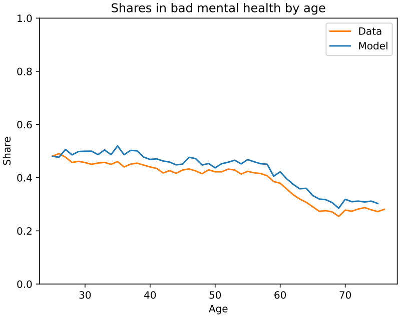
(c) Monthly earnings



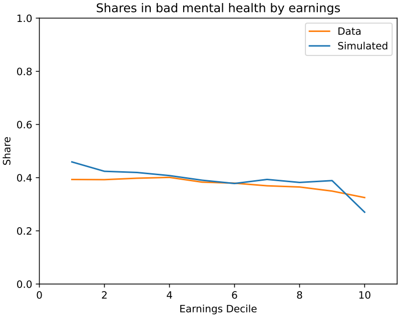
(d) Employment rate

- We entirely miss the extensive margin, the intensive margin fits better.

Shares in bad mental health



(e) Bad MH by age



(f) Bad MH by earnings decile - has more types to smooth

Earnings by health

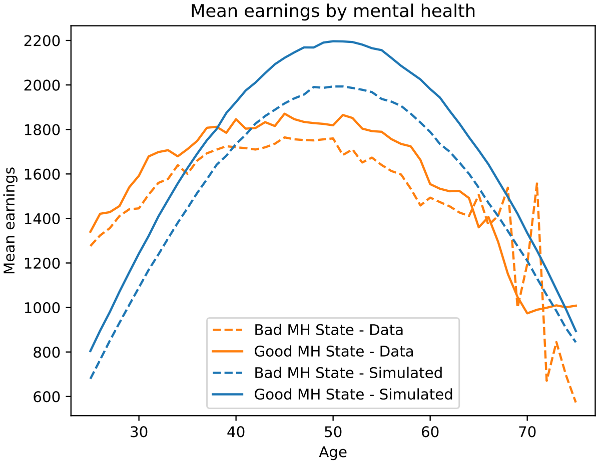
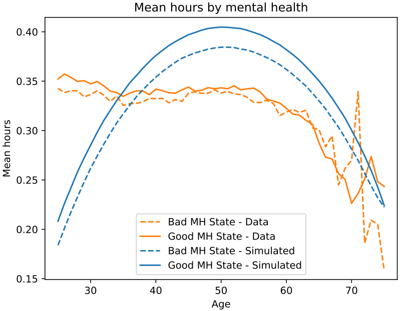


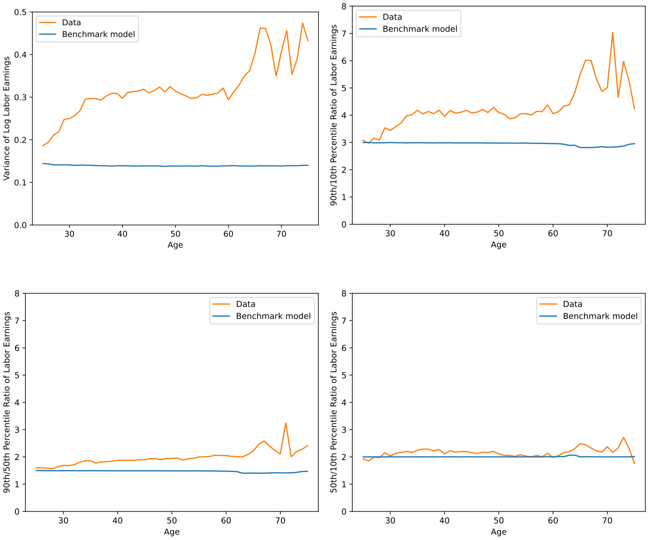
Figure: Mean earnings by MH

- My health states are more different than the data

Wages and hours by health

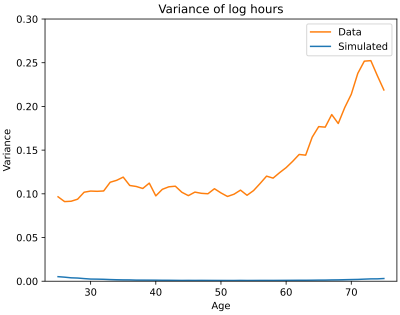


Fit inequality in log earnings

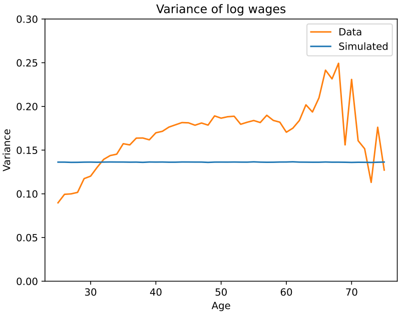


- Does not fit very well

Variance of log hours and log wages



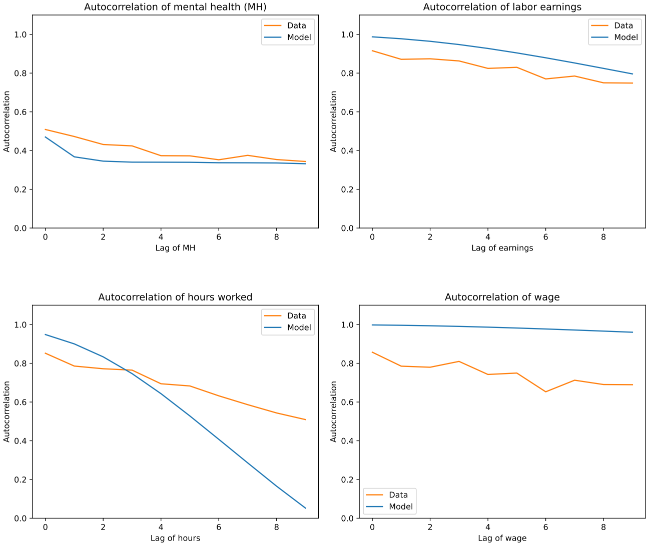
(g) Var of log hours



(h) Var of log wages

- All the action is in hours

Fit persistence



Roadmap

Four counterfactuals

I consider four counterfactuals around mental health

- No time cost: the time cost associated with bad health is set $\phi_H = 0$
- No w_H: the wage coefficient associated with good health is set $w_H = 0$
- All low types: the population share of high health types is set $\omega_{H=Low} = 1.0$
- No mental health: both $\phi_H = 0$ and $w_H = 0$. So that all mental health channels are turned off.

Variance of log earnings counterfactuals

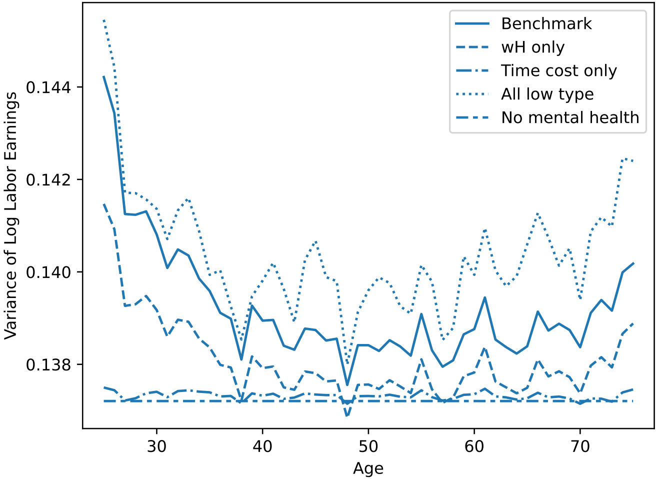
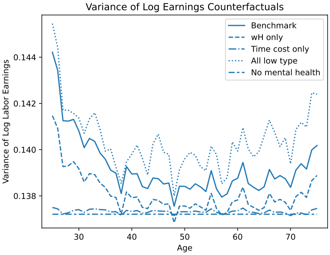
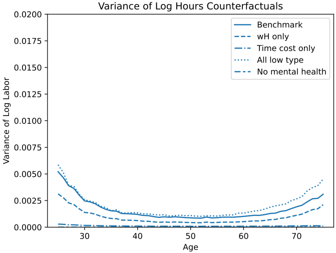
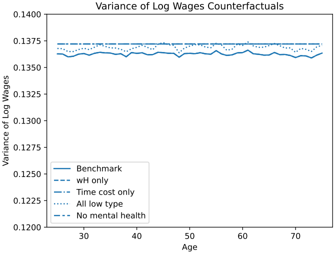


Figure: Variance of log earnings counterfactuals

Decomposing the variance of log earnings







Roadmap

Recap

- Stuff

A culminating idea?

- Stuff

Next steps and direction?

- Stuff

Evidence for next steps?

- E.g. job loss empirically effects mental health
- E.g. finding k^*why not use a latent variables model

Thank You!

Thank you!

Any questions? I appreciate your feedback!

Ratio 90th/50th percentile

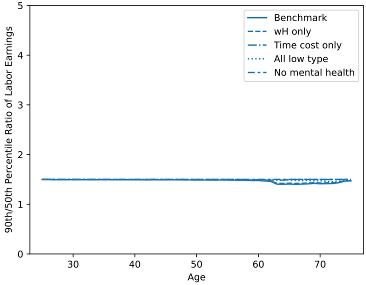


Figure: 90/50 Labor earnings

Ratio 50th/10th percentile

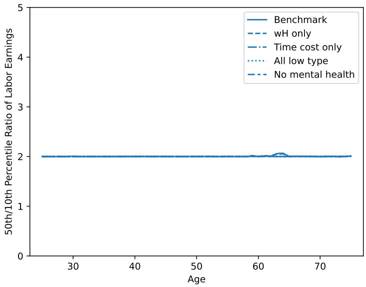


Figure: 50/10 Labor earnings

Some results from a toy calibration?

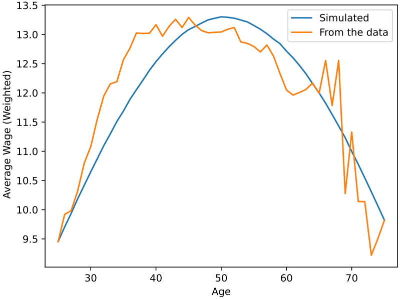
- Maybe not? Maybe if comparative statics become relevant later when estimating different health transitions by type
- i.e. if conditional transitions are more uncertain and comparative statics say something about choices changing with increased uncertainty then this slide could speak to those statics and a calibration with such relatively uncertain transitions

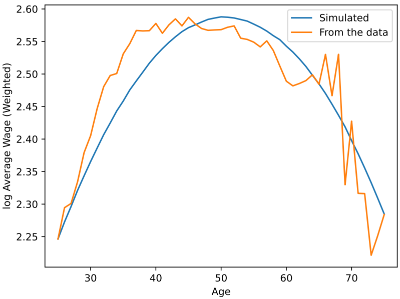
Consider persistent health transitions with moderate uncertainty

$$\Pi_H = \begin{bmatrix} \pi_{B,B}, & \pi_{B,G} \\ \pi_{G,B}, & \pi_{G,G} \end{bmatrix} = \begin{bmatrix} 0.7, & 0.3 \\ 0.3, & 0.7 \end{bmatrix}$$

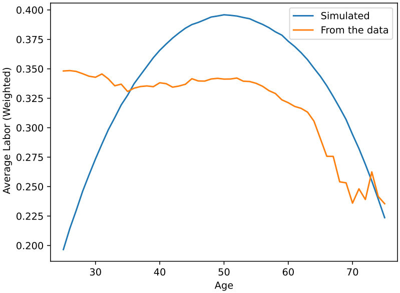
That is a individual has 0.7 chance of remaining in their current health state in the next period.

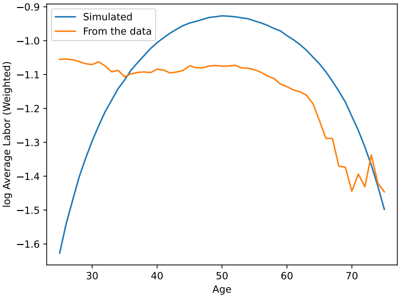
Aggregate wage fit



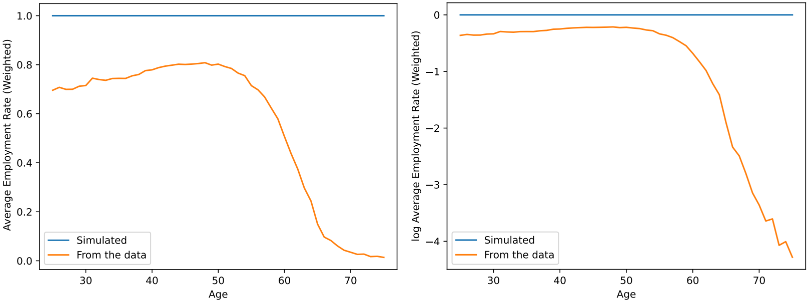


Aggregate labor fit

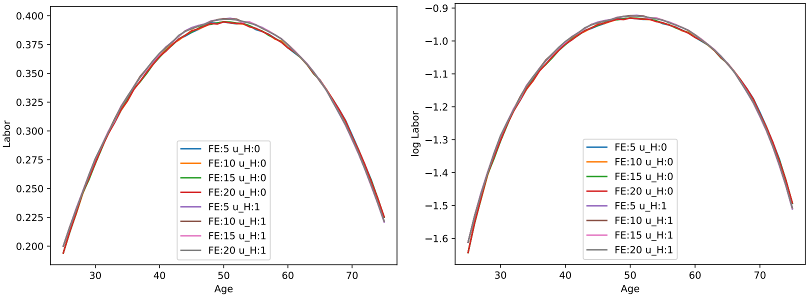




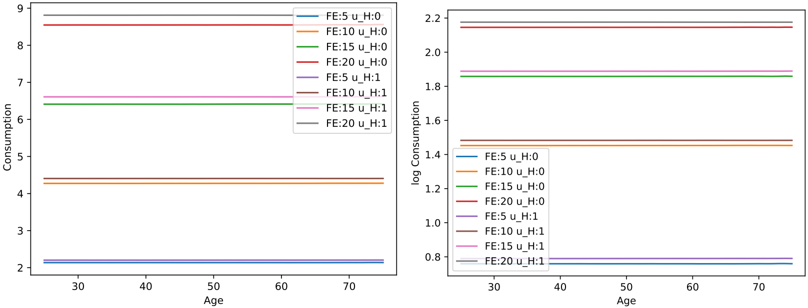
Aggregate employment fit



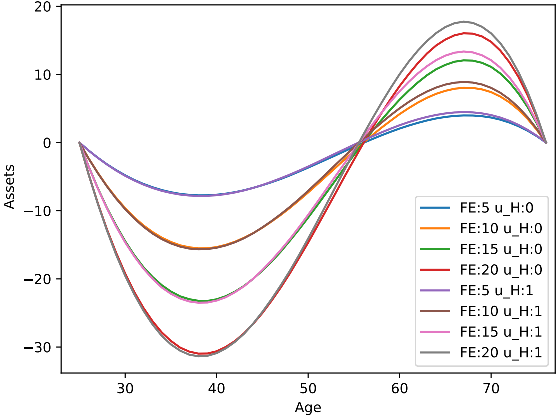
Labor profiles



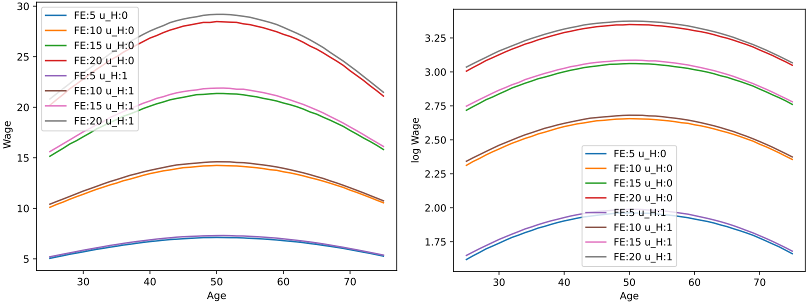
Consumption profiles



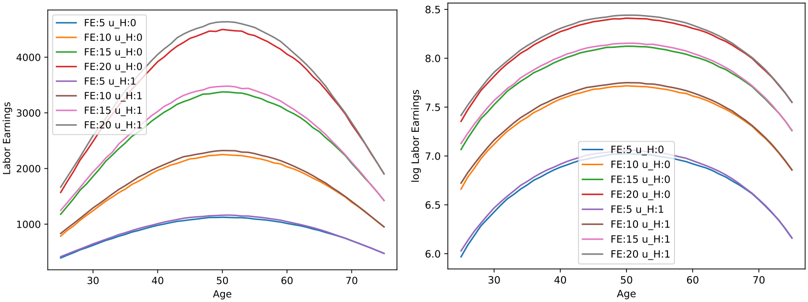
Asset profiles



Wage profiles



Labor income



More on k-means clustering

The goal is to minimize the within-cluster sum of squares:

$$\min \sum_{n=1}^{k} \sum_{\bar{m}_i \in C_n} \|\bar{m}_i - \mu_n\|^2$$

where μ_n is mean of cluster n and $\bar{m}_i$ is an arbitrary data moment: think individual i's mean lifecycle mental health index

1. Randomly select k centroids from the data.
2. Cluster/assign each individual to the nearest centroid.
3. Update centroids by calculating means of clusters
4. Repeat by clustering individuals to the updated centroids
5. Convergence: clusters stablilize.
    1. individuals are consistently assigned to the same cluster

Comparing health transitions

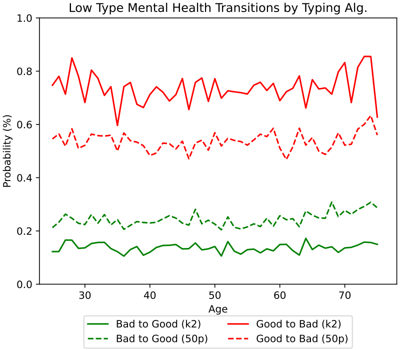
Consider the transition probabilities that result from the two versions of type assignment

Typing Method	Low Type(50.0%)	Bad	Good	High Type(50.0%)	Bad	Good
50pth Cutoff	Bad	0.756	0.244	Bad	0.183	0.817
50pth Cutoff	Good	0.534	0.466	Good	0.098	0.902
Typing Method	Low Type(42.4%)	Bad	Good	High Type(57.6%)	Bad	Good
k-means($k = 2$)	Bad	0.861	0.139	Bad	0.376	0.624
k-means($k = 2$)	Good	0.729	0.271	Good	0.165	0.835

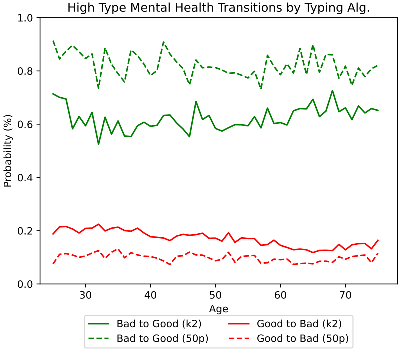
Some text for a footnote?

Table: Health transition matrices by health typing algorithm

Comparing health transitions



(o)



(p)

- compare when conditioned on type to show trajectories not just average probabilities/levels matter by types

Validating health types: explaining health variation

Outcome Variable: Mental Health Index (SF-12)

Lagged MH	x			x	x	-
MH Type 50pth		x		x		-
MH Type k-means ($k = 2$)			x		x	-
R^2	0.374	0.375	0.425	0.461	0.483	-
R^2 with controls	0.382	0.386	0.434	0.466	0.487	0.072

Some text for a footnote.

Table: Validating mental health types

- Health types are just as/more predictive than rich observables

Validating health types: health trajectories

Graph of percentage in bad health over lifecycle by type for 50th percentile type, k-means $k = 2$ $\bar{m}_i$ types, and k-means $k = 2$ h_i types (maybe also $k = k^*$ h_i types but maybe not since comparing apples to oranges)

- The point
  - Types have different trajectories, miss extra variation if only use means and not histories in k-means procedure

References

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- Blundell, Richard et al. (Jan. 2023). "The Impact of Health on Labor Supply near Retirement". In: *Journal of Human Resources* 58.1, pp. 282–334. ISSN: 0022166X. DOI: 10.3368/jhr.58.3.1217-9240r4. URL: http://proxy.library.vanderbilt.edu/login?url=https: