Mental health and lifecycle inequality

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Roadmap

Introduction and motivation

Data and preliminary evidence

Lifecycle model

Mental health process and types (estimation?)

Model estimation and validation

Results (counterfactuals?)

Conclusion

Question(s)

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

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

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

Motivation

How stuff

- Stuff

Some literature

- Mental health
  - E.g. Abramson et al. (2024), Jolivet and Postel-Vinay (2020), Cronin et al. (2023)
- Physical health
  - E.g. Borella et al. (2024),De Nardi et al. (2021), Hosseini et al. (2021)

Blank

- Stuff

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SF12 and UKHLS

- Stuff

MH affects labor outcomes

- Stuff

Blank

- Stuff

Roadmap

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 and time endowment
- 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. Health status $H \sim \Pi_H$ which can be conditioned on u_H and age j.

Consumption constraints

Choices must be s.t.

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

$$a_0 = a_{J+1} = 0;$$

and

$$a_j > -\kappa, \text{ and } c_j, n_j \geq 0; \forall j.$$

With $\ln z(\gamma, j, H) = w_{0\gamma_i} + w_1 j + w_2 j^2 + w_H 1_{H=Bad}$ where the linear coefficient depends on productivity type γ_i. κ is the borrowing constraint.

HH recursive optimization problem

The individual's problem:

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

s.t.

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

and

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

$$H' \sim \Pi_H$$

Health transitions

Health evolves according to the transition matrix

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

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

These probabilities can be conditioned on age j and permanent health type. E.g. $u_H \in \{u_{Low}, u_{High}\}$

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

Roadmap

Health states

- Two health states $H \in \{Bad, Good\}$
- To inform the cut off I run the following quantile regression
- Quantile regression?
- Suggests below 40th percentile is *Bad*

Health states and process

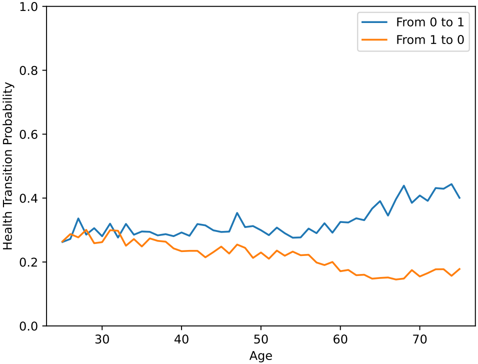
- Individuals are said to be in $H = Bad$ health if they are below the 40th percentile of the mental health index. $H = Good$ otherwise.
- I estimate the transition probabilities as the fraction of individuals that make the relevant transition.
  - E.g. the estimated unconditional probability $\hat{\pi}_{B,G}$ 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.

Unconditional transitions

Calculating the health state transition matrix without conditioning on type or age yields

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

Unconditional transitions by age



- the point
  - show that health trajectories are dynamic over the lifecycle
  - compare when conditioned on type to show trajectories not just average probabilities matter by types

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.
- Let $\bar{m}_i$ be the individuals mean mental health index value over their lifecycle
- I consider two ways to establish a cut off using this moment
  - Percentile cutoff: select a threshold percentile p_m over the $\bar{m}_i$s. Assign $u_{H,i} = \begin{cases} u_{Low} & \text{if } \bar{m}_i < p_m \\ u_{High} & else \end{cases}$ e.g $p_m =$ the 50th percentile.
  - K-Means clustering: a machine learning algorithm that partitions the data into k non-overlapping clusters. Goal is to group data s.t. that within group data points are more similar to each other than to other data points.

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

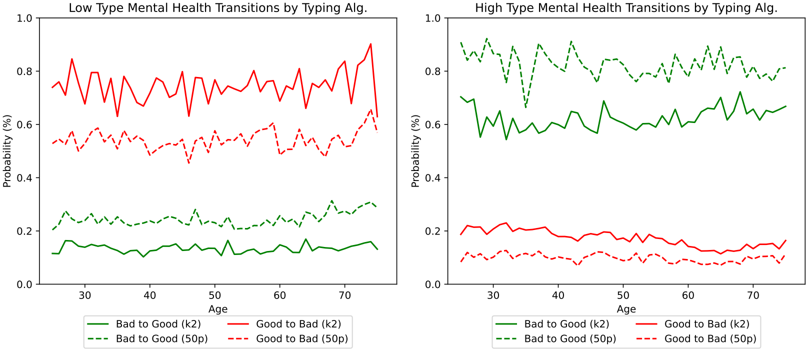
Consider the transition probabilities that result from the two versions of type assignment

Typing Method	Low Type(50.0%)	Bad	Good	High Type(50.0%)	Bad	Good
50pth Cutoff	Bad	0.757	0.243	Bad	0.18	0.82
50pth Cutoff	Good	0.539	0.461	Good	0.097	0.903
Typing Method	Low Type(28.8%)	Bad	Good	High Type(71.2%)	Bad	Good
k-means($k=2$)	Bad	0.864	0.136	Bad	0.377	0.623
k-means($k=2$)	Good	0.738	0.262	Good	0.166	0.834

Some text for a footnote?

Table: Health transition matrices by health typing algorithm

Comparing health transitions



(a) (b)

- 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	0.373	0.378	0.43	0.461	0.484	-
R^2 with controls	0.381	0.389	0.439	0.466	0.489	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

Improving typing

Types

- Physical health types shown in Borella et al. (2024) to be better predictors of physical health than rich set of observable
- Use k-means clustering on health histories/trajectories earlier in life to determine health types used in health process
- Leverage health histories
- Systematically determine number of health types

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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	0.1	Benchmark
$\omega_{H=0}$	Low type pop. weight	0.2877	UKHLS
$\omega_{H=1}$	High type pop. weight	0.7123	$1-\omega_{H=0}$

Table: Exogenous parameters

Calibrated parameters

Parameter	Description	Par. Value	Target Moment	Target Value	Model Value
α	c utility weight	0.375	Mean hours worked	31.85	31.86
w_1	Linear wage coeff.	0.026	Wage growth	33.73%	33.71%
w_2	Quad. wage coeff.	-0.0005	Wage decay	28.87%	28.88%
w_H	Health wage coeff.	0.0415	Healthy wage premium	4.35%	4.27%

Table: Calibrated parameters 1

Calibrated parameters

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, $j = 0$	9.458	9.458	
SD wage, $j = 0$	3.202	3.202	

Table: Calibrated parameters 2

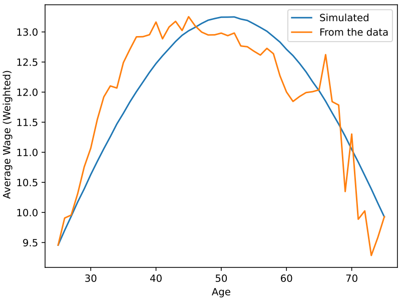
Wage trimming

- Drop if mental health index missing
- Drop if longitudinal weight is missing or negative
- Drop if missing age
- Drop if employed and wage $<$ half UK minimum wage (half of 11.44 pounds)
- Drop if work less than 10 hours a week
- I do not but can drop wages $>$ 0.1% to further smooth the wage profile (especially post/near retirement)
- Survey data, sometimes same age in neighboring observations... drop those after the duplicate age occurs.

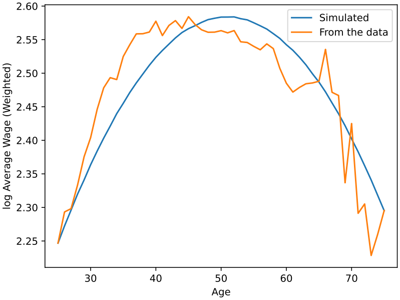
Validation

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

Aggregate wage fit



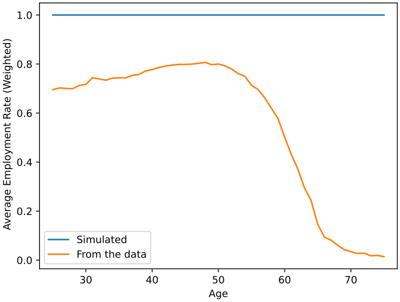
(c) Wage



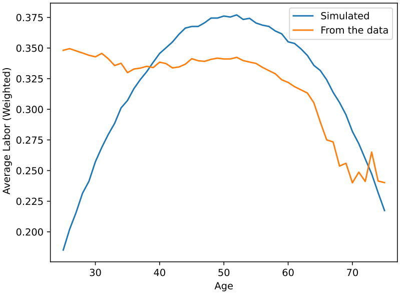
(d) Log wage

- Unsurprisingly wage fits well

Aggregate labor supply and employment rate fit



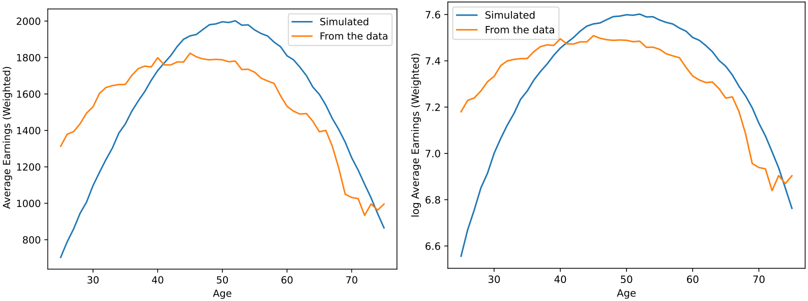
(e) Employment rate



(f) Hours worked (labor)

- The point while we do not fit the extensive margin very well, the intensive margin fits better.

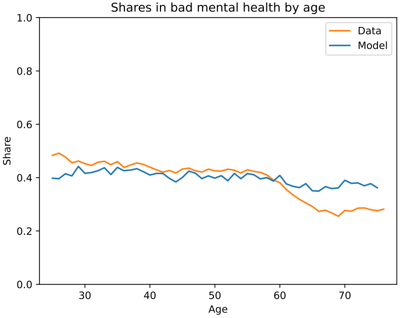
Aggregate labor earnings fit



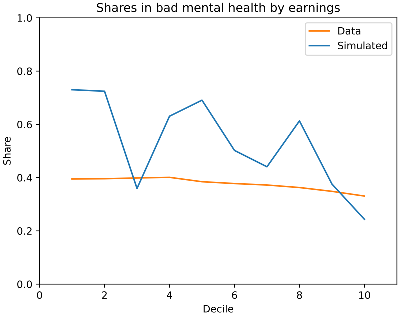
(g) Earnings (h) Log earnings

- Unsurprisingly fits well given wage fit

Shares in bad mental health



(i) Bad MH by age



(j) Bad MH by earnings decile

- Maybe deciles are bad? or need more types?

Earnings by health

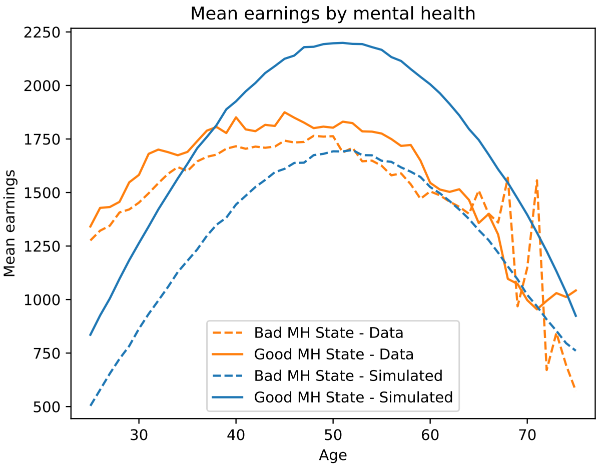
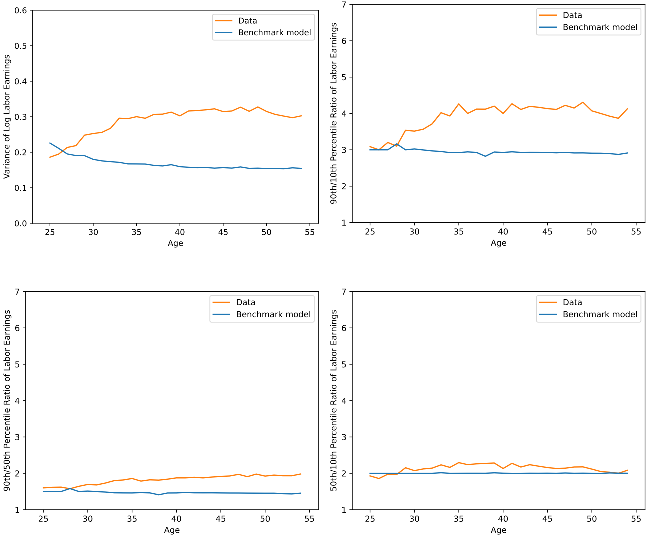


Figure: Mean earnings by MH

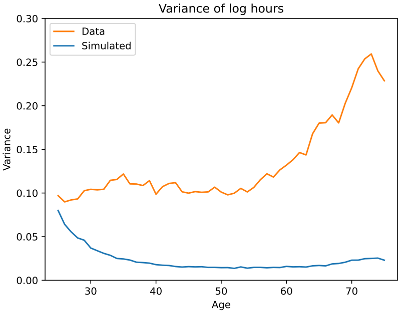
- My health states are more different than the data

Fit inequality in log earnings

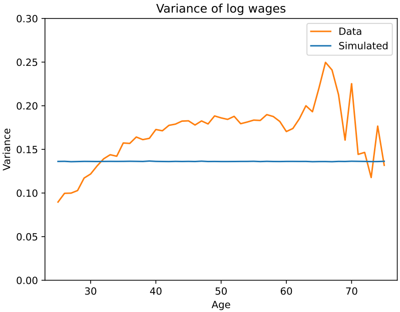


- Does not fit very well

Variance of log hours and log wages



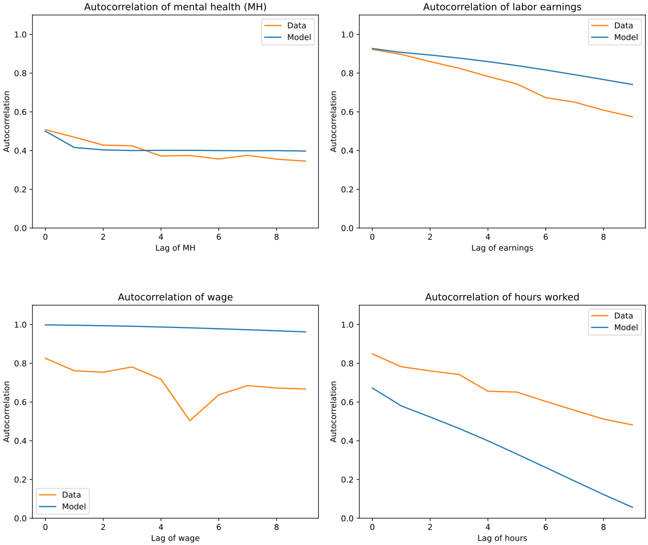
(e) Var of log hours



(f) 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 high types: the population share of high health types is set $\omega_{H=good} = 1.0$
- 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

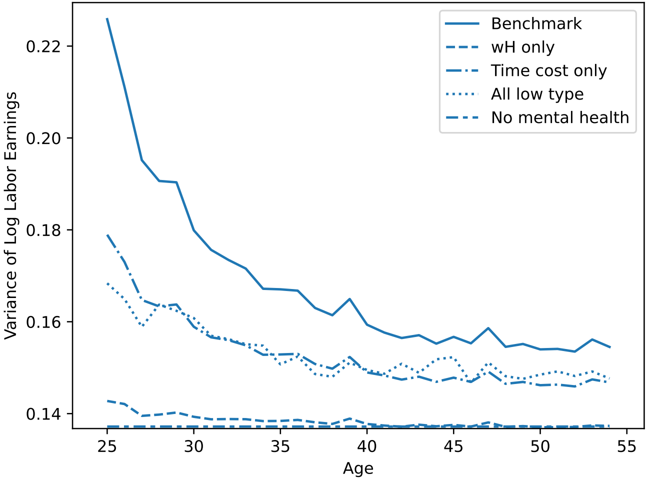
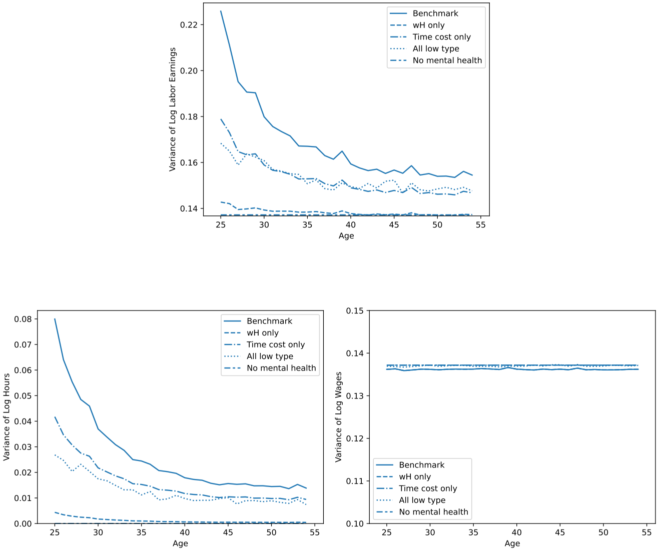
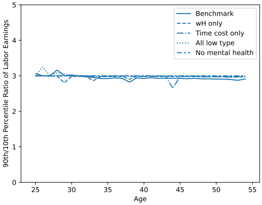


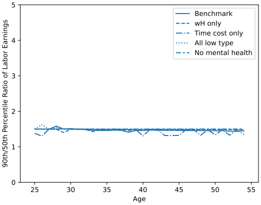
Figure: Variance of log earnings counterfactuals

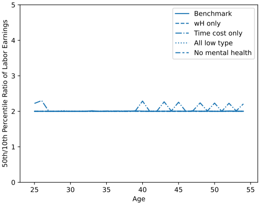
Decomposing the variance of log earnings



Percentile ratios of earnings







(e) 90/10 Labor earnings (f) 90/50 Labor earnings (g) 50/10 Labor earnings

Evaluating mental health mechanisms: wage

- Table and/or graphs compare moments like hours worked, income, wealth, consumption... maybe also calibrated parameters?
- Variance of accumulated earnings or wealth also? or save for final graph?

Evaluating mental health mechanisms: time cost

- Table and/or graphs compare moments like hours worked, income, wealth, consumption... maybe also calibrated parameters?
- Variance of accumulated earnings or wealth also? or save for final graph?

Impact of mental health inequality

- Estimate a life-cycle model of consumption, labor, wealth with heterogeneous MH
- Run counterfactuals with no MH inequality, compare earnings/labor inequality
    - Does this mean turn off both channels? or make everyone healthy state all the time?
    - Alternatively make everyone best mental health type

How important is mental health inequality for lifecycle inequality?

- Graph of variance of lifetime earnings over the lifecycle
- One line with mental health inequality and permanent heath types
- One line with mental health inequality and no permanent heath types
- One line with no health inequality

How important is mental health inequality for lifecycle inequality?

- Discussion of the above graph

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

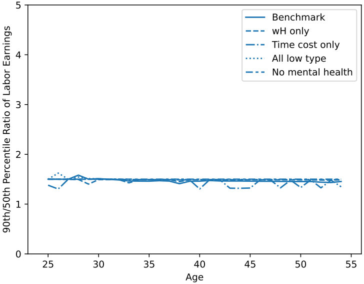


Figure: 90/50 Labor earnings

Ratio 50th/10th percentile

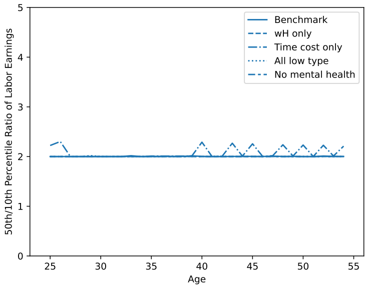


Figure: 50/10 Labor earnings

Some results from a toy calibration?

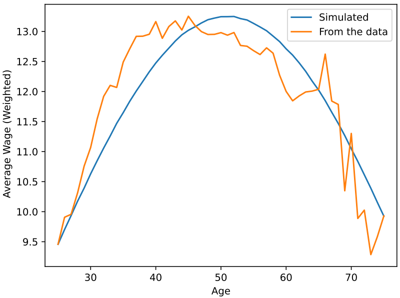
- Maybe not? Maybe if comparative statics become relevant later when estimating different health transitions by type
- i.e. if conditional transitions are more uncertain and comparative statics say something about choices changing with increased uncertainty then this slide could speak to those statics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

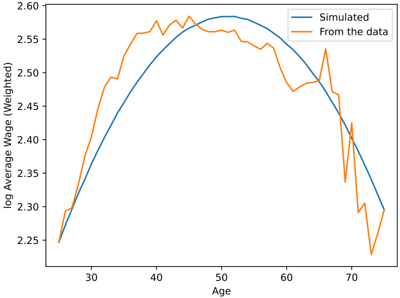
Consider persistent health transitions with moderate uncertainty

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

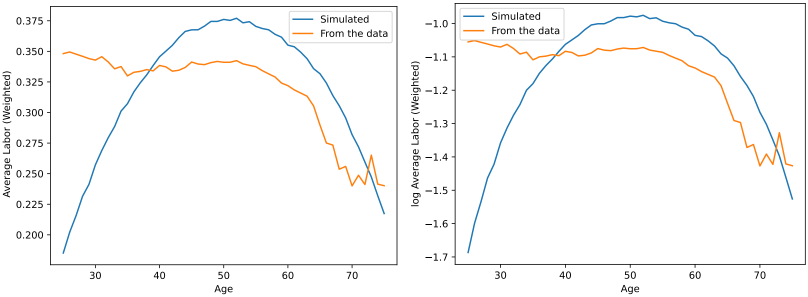
That is a individual has 0.7 chance of remaining in their current health state in the next period.

Aggregate wage fit

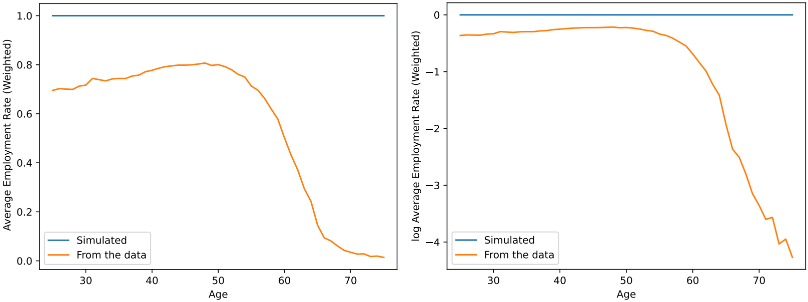




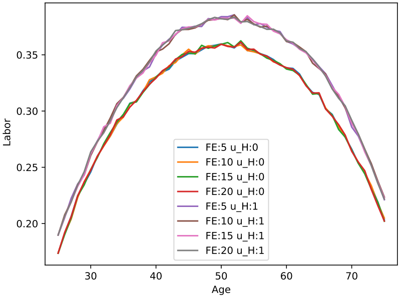
Aggregate labor fit

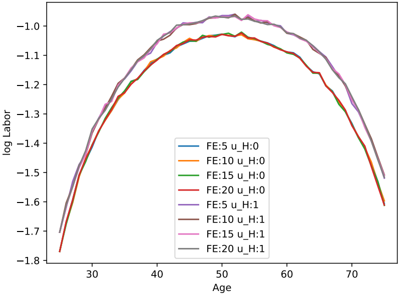


Aggregate employment fit

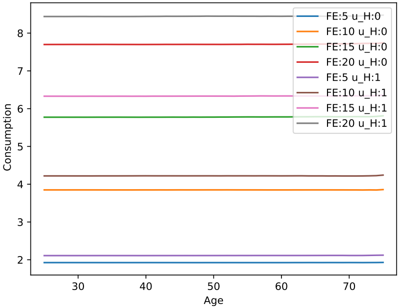


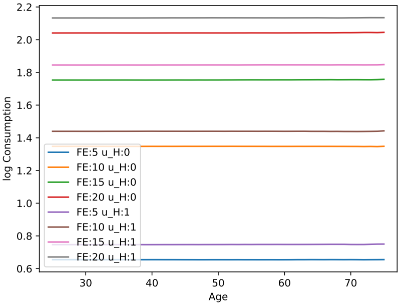
Labor profiles



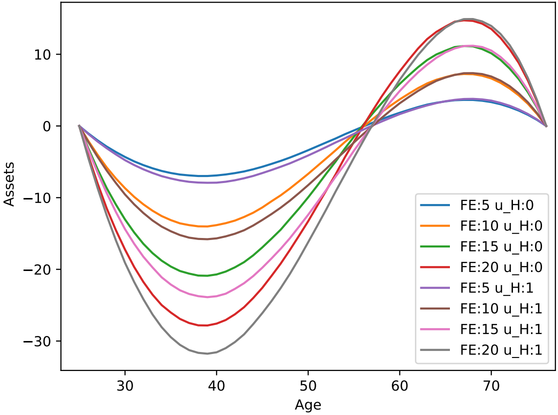


Consumption profiles

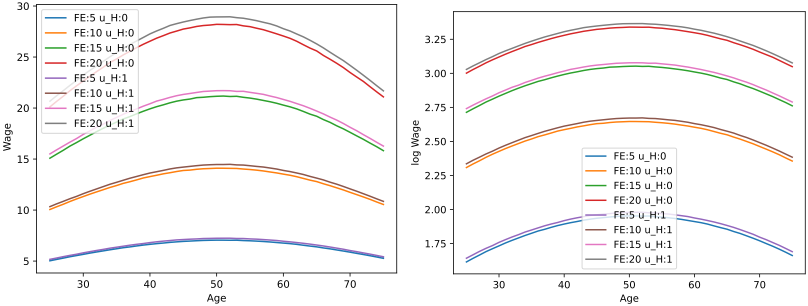




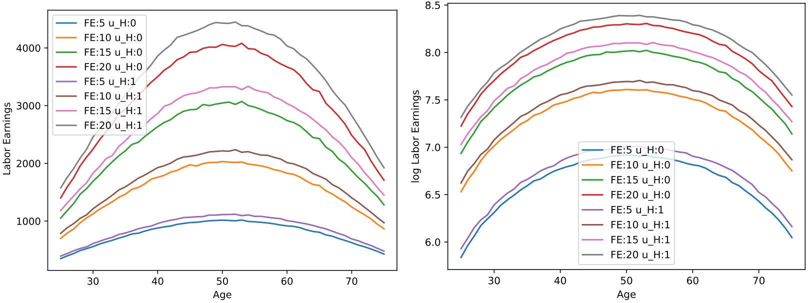
Asset profiles



Wage profiles



Labor income



Extra frame

1. Extra stuff

References

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