

# Mental health and lifecycle inequality

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# Roadmap

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Introduction and motivation

Data and preliminary evidence

Lifecycle model

Mental health process and types (estimation?)

Model estimation and validation

Results (counterfactuals?)

Conclusion

## Question(s)

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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

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How stuff

- Stuff

## Some literature

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- 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)

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- Stuff

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- Stuff



## MH affects labor outcomes

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- Stuff

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- Stuff

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## Model in words

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- 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  $\gamma$  effects the wage process
  - Health type  $u_H$  which effects health transition probabilities

## Utility and time endowment

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Individuals derive period utility from consumption and leisure

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

where the time endowment is s.t.

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

$\phi_n$  the time cost of work  $> 1$  to account for commuting etc,  $\phi_H$  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

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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  $\ln z(\gamma, j, H) = w_0\gamma_i + w_1j + w_2j^2 + w_H1_{H=Bad}$  where the linear coefficient depends on productivity type  $\gamma_i$ .  $\kappa$  is the borrowing constraint.

## HH recursive optimization problem

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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

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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  $H = \textit{Bad}$  to  $H = \textit{Good}$ .

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

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



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## Health states

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- 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

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- Individuals are said to be in  $H = \textit{Bad}$  health if they are below the 40th percentile of the mental health index.  $H = \textit{Good}$  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.
  - $\hat{\pi}_{B,G}^{u_H}$  is the fraction of people who are the permanent good health type who transition from bad to good health.
  - $\hat{\pi}_{B,G}^{u_H,j}$  is the fraction of people of age  $j$  who are the permanent good health type who transition from bad to good health.

## Unconditional transitions

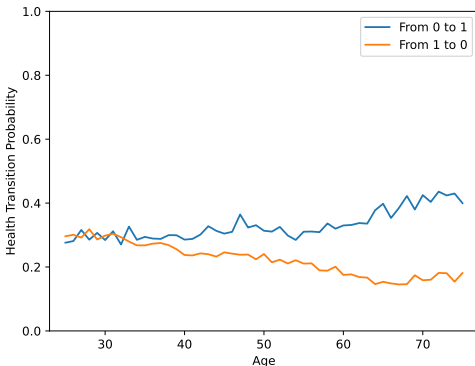
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Calculating the health state transition matrix without conditioning on type or age yields

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

# Unconditional transitions by age

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- 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

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- 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  $u_{H,i} = \begin{cases} u_{Low} & \text{if } \bar{m}_i < p_m \\ u_{High} & \text{else} \end{cases}$  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

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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  $\mu_n$  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 stabilize.
  - ① individuals are consistently assigned to the same cluster

# Comparing health transitions

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

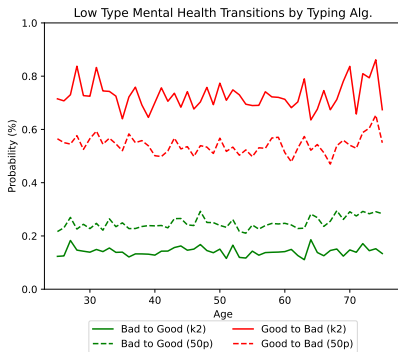
Typing Method	Low Type(50.0%)	Bad	Good	High Type(50.0%)	Bad	Good
50pth Cutoff	Bad	0.751	0.249	Bad	0.193	0.807
50pth Cutoff	Good	0.537	0.463	Good	0.1	0.9
Typing Method	Low Type(28.9%)	Bad	Good	High Type(71.1%)	Bad	Good
$k$ -means( $k = 2$ )	Bad	0.856	0.144	Bad	0.379	0.621
$k$ -means( $k = 2$ )	Good	0.721	0.279	Good	0.169	0.831

Some text for a footnote?

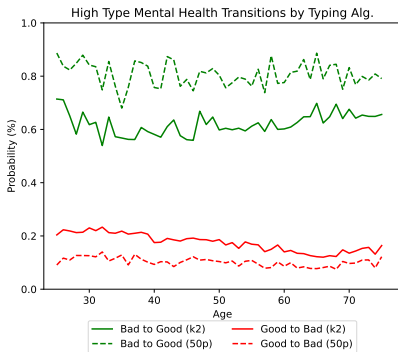
**Table:** Health transition matrices by health typing algorithm



# 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

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*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	-
$R^2$	0.368	0.366	0.414	0.455	0.476	-
$R^2$ with controls	0.376	0.378	0.424	0.46	0.48	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

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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

### 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

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Parameter	Description	Value	Source
$R$	Gross interest rate	1.02	Benchmark
$\beta$	Patience	0.9804	$1/R$
$\sigma$	CRRA	0.9999	Benchmark
$\phi_n$	Labor time-cost	1.125	Benchmark
$\phi_H$	Health time-cost	0.1	Benchmark
$\omega_{H=0}$	Low type pop. weight	0.2894	UKHLS
$\omega_{H=1}$	High type pop. weight	0.7106	$1 - \omega_{H=0}$

Table: Exogenous parameters

# Calibrated parameters

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Parameter	Description	Par. Value	Target Moment	Target Value	Model Value
$\alpha$	$c$ utility weight	0.3633	Mean hours worked	30.87	30.94
$w_1$	Linear wage coeff.	0.0258	Wage growth	33.89%	33.89%
$w_2$	Quad. wage coeff.	-0.0005	Wage decay	27.41%	27.37%
$w_H$	Health wage coeff.	0.0415	Healthy wage premium	4.42%	4.33%

Table: Calibrated parameters 1

## Calibrated parameters

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Constant wage coeff.	Ability Level	Value	Weight
$w_{0\gamma_1}$	Low	5	0.35
$w_{0\gamma_2}$	Medium	10	0.45
$w_{0\gamma_3}$	Medium High	15	0.18
$w_{0\gamma_4}$	High	20	0.02
Target Moment	Target Value	Model Value	
Mean wage, $j = 0$	9.593	9.593	
SD wage, $j = 0$	3.936	3.935	

Table: Calibrated parameters 2

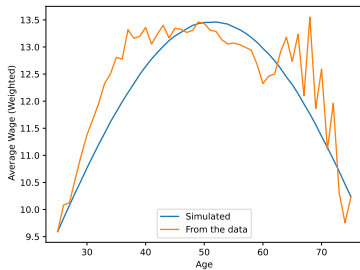


# Validation

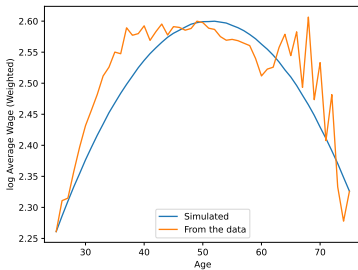
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- Evaluate fit of non targeted moments (especially by health type and by health state)
- Consumption, labor income, wealth/savings, labor participation

# Aggregate wage fit



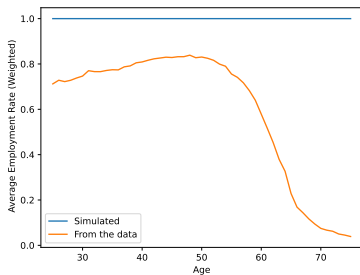
(c)



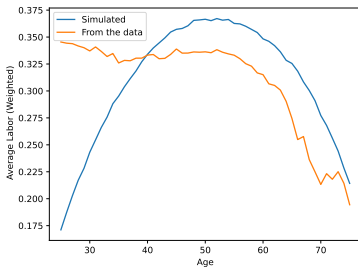
(d)

- Unsurprisingly wage fits well

# Aggregate labor supply and employment rate fit



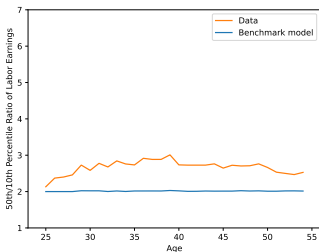
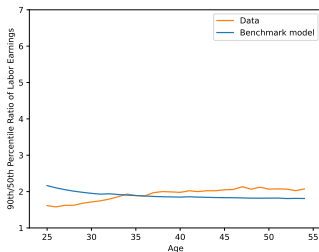
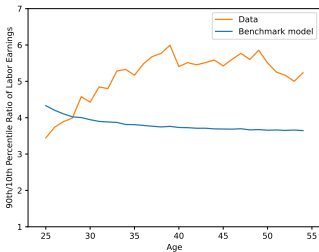
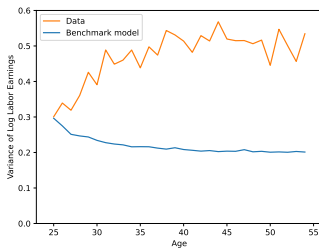
(e)



(f)

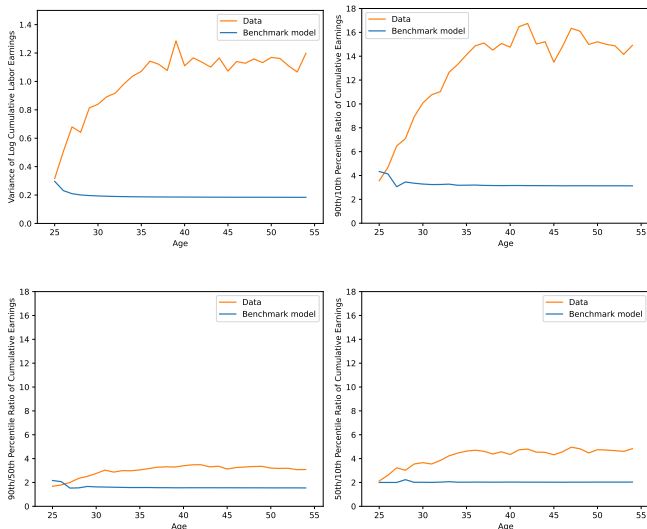
- The point

# Fit inequality in log earnings



- Does not fit very well

# Fit inequality in log cumulative earnings



- Does not fit very well

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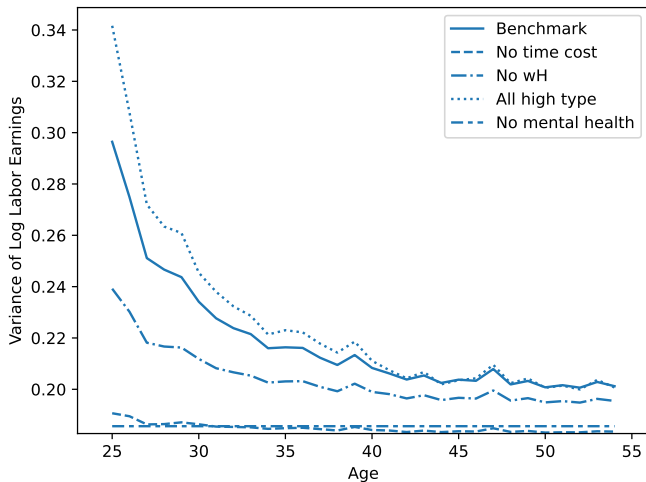
## Four counterfactuals

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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.

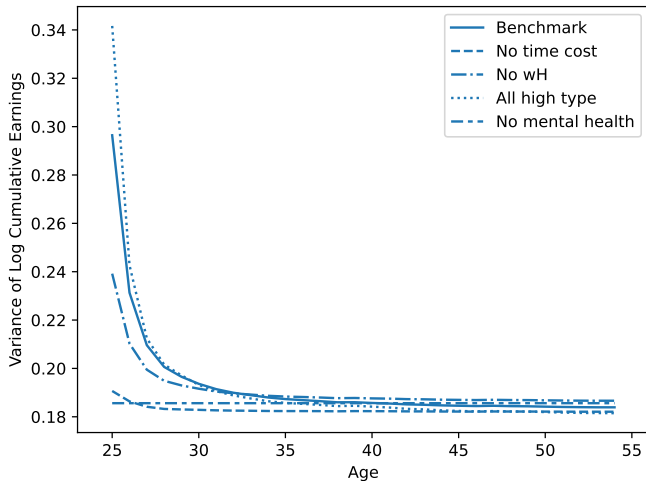
## Variance of log earnings



Figure

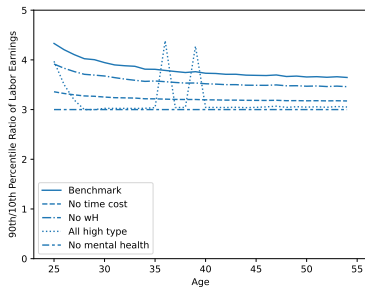


# Variance of cumulative log earnings

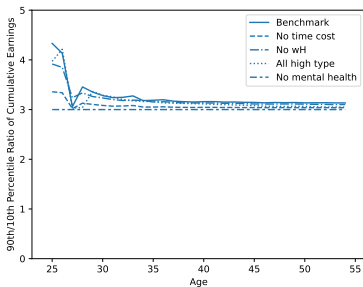


Figure

# Ratio 90th/10th percentile

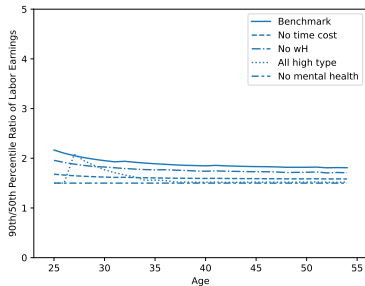


(a) Labor earnings

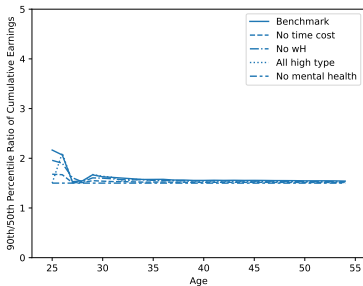


(b) Cumulative labor earnings

# Ratio 50th/10th percentile

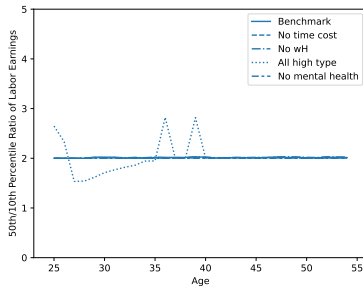


(c) Labor earnings

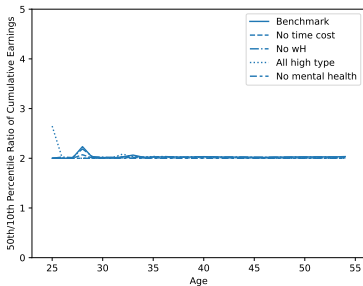


(d) Cumulative labor earnings

# Ratio 50th/10th percentile



(e) Labor earnings



(f) Cumulative labor earnings

## Evaluating mental health mechanisms: wage

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- 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

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- 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

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- 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?

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



## How important is mental health inequality for lifecycle inequality?

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- Discussion of the above graph

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# Recap

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- Stuff

## A culminating idea?

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- Stuff

## Next steps and direction?

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- Stuff

## Evidence for next steps?

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

# Thank You!

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**Thank you!**

Any questions? I appreciate your feedback!

## Some results from a toy calibration?

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- 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

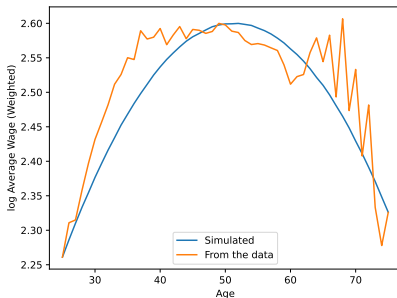
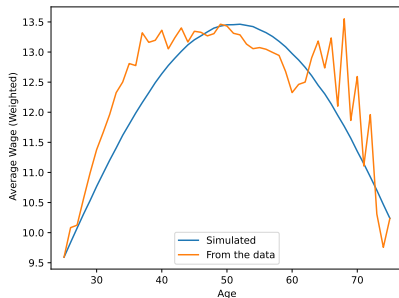
$$\Pi_H = \begin{bmatrix} \pi_{B,B} & \pi_{B,G} \\ \pi_{G,B} & \pi_{G,G} \end{bmatrix} = \begin{bmatrix} 0.7 & 0.3 \\ 0.3 & 0.7 \end{bmatrix}$$

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

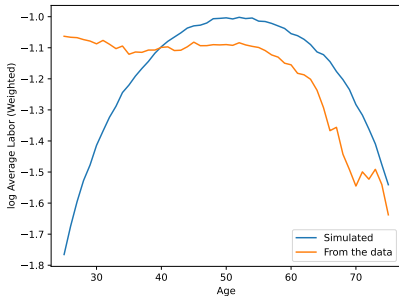
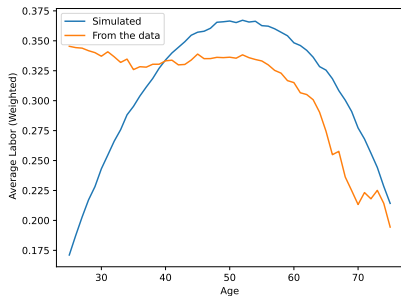


# Aggregate wage fit

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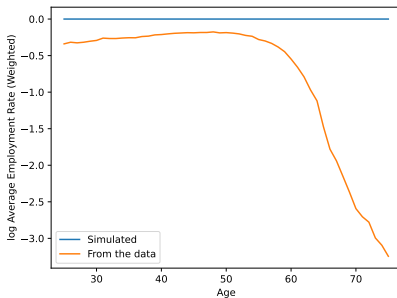
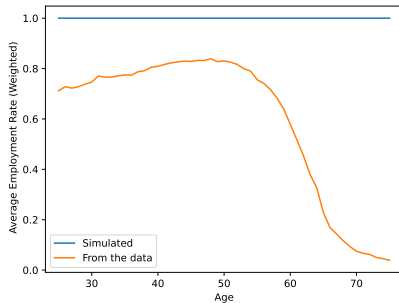


# Aggregate labor fit



# Aggregate employment fit

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## Labor profiles

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## Consumption profiles

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## Asset profiles

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## Wage profiles

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## Labor income

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## Extra frame

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- ① Extra stuff

## References

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