

# Lifecycle mental health and earnings inequality

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# Roadmap

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Introduction & Data

Lifecycle model

Model estimation and validation

Counterfactuals

# Motivation

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## Why mental health (MH)?

- Prevalent and costly (Direct costs, Indirect costs)
- US: 20% adults experience mental illness each year (NSDUH) (NIMH)
- UK: 65% of adults in the UK have experienced some mental health problem (UKMHF)
  - 40% of adults have experienced depression, 25% a panic attack
  - Notably 85% of adults out of work have experienced a mental health problem,
    - 65% of the in work, 50% of the retired

## Why MH and labor?

- Policy makers care but difficult to evaluate (WHO, 2023), (OECD)
- Evaluate policy by health and labor outcomes
  - mean levels and spread or inequality.
- Large (mostly physical) health and lifecycle labor literature

# Health and labor literature

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- Physical health and labor: empirical
  - Health effects labor, justify single index: Bound et al. (1999), Blundell et al. (2023)
  - Labor effects PH somewhat (mostly risky behavior & MH) Schaller and Stevens (2015)
- Large physical health and the lifecycle
  - Health, wealth and retirement: French (2005)
  - Continuous PH: Hosseini et al. (2021), Dal Bianco and Moro (2022)
  - Unobserved types: De Nardi et al. (2021)
- Mental health and labor: empirical
  - MH effects employment, maybe in NLSY79: Germinario et al. (2022)
  - MH effects career trajectory: Biasi et al. (2021)
  - Work autonomy effects MH: Spearing (2024)
- Newer mental health and labor: structural
  - Macro of mental health: Abramson et al. (2024)
  - MH treatment: Cronin et al. (2023)
  - Job search, stress and MH: Jolivet and Postel-Vinay (2020)

## Questions and methods

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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
- How does physical health fit in?

Note:

$$Earnings = Employed * Hours * Wage$$

# SF12 and UKHLS Panel

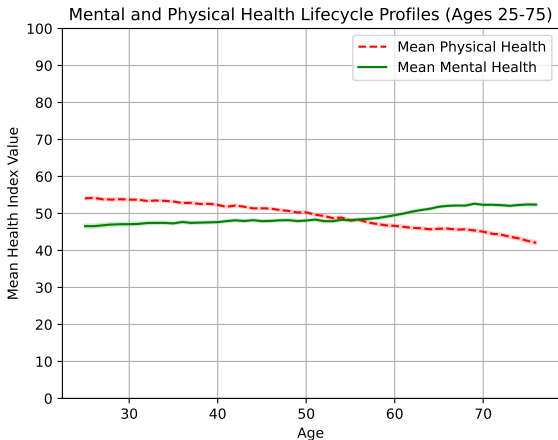
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Table 12: SF-12 Questionnaire

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 your health interfere with your social life?

- UKHLS: United Kingdom Household Longitudinal Survey
- Nationally representative panel survey with health, income, employment, hours, demographics, time use etc.
- Sample is individuals aged 25-75 in the UK between 2009 and 2021
- 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).

# Mean Health Over the Lifecycle



- Index is standardized to a 50 pt. mean and 10 pt. standard deviation
- MH increases by about 1 std. dev., while PH decreases by about 1.5 std. dev. from 25-75

# MH affects labor outcomes

Mental and Physical Health Indices and Labor Outcomes

	Year FE				Individ and Year FE			
	Employment	ln(Earnings)	ln(Wage)	ln(Hours)	Employment	ln(Earnings)	ln(Wage)	ln(Hours)
Mental Health	0.01677*** (0.000)	0.00212 (0.001)	0.00263** (0.001)	-0.00050 (0.001)	0.00338*** (0.000)	-0.00090 (0.001)	0.00111 (0.001)	-0.00201*** (0.001)
Physical Health	0.01923*** (0.000)	0.00630*** (0.001)	0.00584*** (0.001)	0.00046 (0.001)	0.00387*** (0.000)	-0.00080 (0.001)	0.00094 (0.001)	-0.00175** (0.001)
MH × PH	-0.00023*** (0.000)	0.00001 (0.000)	-0.00001 (0.000)	0.00002 (0.000)	-0.00004*** (0.000)	0.00001 (0.000)	-0.00001 (0.000)	0.00003** (0.000)
female	-0.08798*** (0.002)	-0.41398*** (0.004)	-0.14776*** (0.003)	-0.26622*** (0.002)	0.00214 (0.050)	0.20999* (0.082)	0.10675* (0.052)	0.10324 (0.062)
College	0.06733*** (0.002)	0.36049*** (0.004)	0.30941*** (0.003)	0.05108*** (0.002)	0.09178*** (0.019)	0.06414** (0.021)	0.01899 (0.018)	0.04514** (0.015)
Observations	142,051	76,849	76,849	76,849	136,648	73,068	73,068	73,068
R-Square	0.40755	0.31907	0.26407	0.19929	0.80056	0.88147	0.82475	0.79041
Adj. R-Square	0.40737	0.31869	0.26366	0.19884	0.77397	0.85690	0.78843	0.74698

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

- PH and MH differentially effect labor market outcomes
- Individual FE: unobserved fixed heterogeneity seems important



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## Model in one slide: 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  $w_H$
- Permanent labor productivity type  $\gamma$  effects the wage process

# 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.

$$l_j = 1 - \phi_n n_j$$

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

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

$$\begin{aligned} V_j(a, \gamma, H) &= \max_{c, n, a'} \{u(c, 1 - \phi_n n) + \beta \mathbb{E}_{H'} V_{j+1}(a', \gamma, H')\} \\ \text{s.t. } c + a' &= z(\gamma, j, H) \cdot n + a(1 + r); \forall j \\ \ln z(\gamma_i, j, H_{ij}) &= w_0 \gamma_i + w_1 j + w_2 j^2 + w_H 1_{H_{ij}=\text{Good}} \end{aligned} \quad (1)$$

$$H' \sim \Pi^H \quad (2)$$

$w_0 \gamma_i$  depends on productivity type  $\gamma_i$ .

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

# Establishing and good and bad mental health

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*** (0.008)	0.006 (0.018)	0.012 (0.013)	-0.006 (0.013)	0.033*** (0.005)	-0.001 (0.010)	0.013 (0.009)	-0.014 (0.008)
Good Mental Health	0.269*** (0.009)	0.034 (0.020)	0.032* (0.014)	0.002 (0.014)	0.046*** (0.006)	-0.003 (0.010)	0.016 (0.009)	-0.018* (0.008)
Very Good MH	0.305*** (0.010)	0.087*** (0.022)	0.076*** (0.016)	0.011 (0.015)	0.060*** (0.007)	0.002 (0.012)	0.023* (0.010)	-0.021* (0.009)
Excellent Mental Health	0.320*** (0.007)	0.059*** (0.017)	0.060*** (0.013)	-0.001 (0.012)	0.051*** (0.006)	0.002 (0.010)	0.016 (0.009)	-0.014 (0.008)
Fair Physical Health	0.243*** (0.009)	0.056** (0.017)	0.047*** (0.013)	0.010 (0.012)	0.044*** (0.007)	0.014 (0.009)	0.017* (0.008)	-0.003 (0.008)
Good Physical Health	0.344*** (0.011)	0.073*** (0.017)	0.064*** (0.013)	0.009 (0.013)	0.062*** (0.008)	0.012 (0.010)	0.022* (0.009)	-0.010 (0.008)
Very Good PH	0.351*** (0.013)	0.098*** (0.019)	0.080*** (0.015)	0.018 (0.014)	0.038*** (0.010)	0.017 (0.011)	0.024* (0.010)	-0.008 (0.009)
Excellent Physical Health	0.398*** (0.008)	0.166*** (0.015)	0.140*** (0.011)	0.026* (0.011)	0.060*** (0.007)	-0.001 (0.009)	0.019* (0.008)	-0.020** (0.007)
female	-0.090*** (0.002)	-0.416*** (0.004)	-0.150*** (0.003)	-0.266*** (0.002)	0.002 (0.050)	0.210* (0.082)	0.107* (0.052)	0.104 (0.061)
College	0.070*** (0.003)	0.359*** (0.004)	0.308*** (0.003)	0.051*** (0.002)	0.086*** (0.019)	0.066** (0.021)	0.021 (0.018)	0.045** (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

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- 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

## Health states and process

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Health evolves according to the transition matrix

$$\Pi_j^H = \begin{bmatrix} \pi_j^{BB}, & \pi_j^{BG} \\ \pi_j^{GB}, & \pi_j^{GG} \end{bmatrix}$$

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

- $H = Bad$  if 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.  $\hat{\pi}_j^{BG}$  is the fraction of people who transition from bad to good health at age  $j$



## Unconditional transitions by age

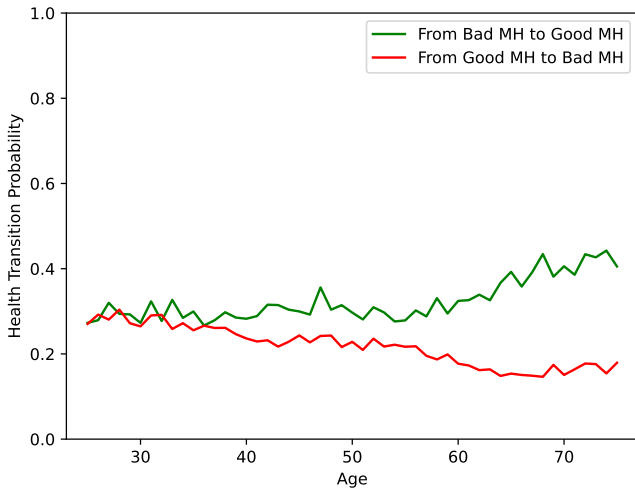


Figure: 1-Year Mental Health Transitions

# Roadmap

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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

Table: Exogenous parameters

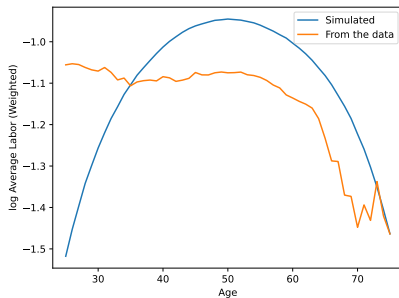
# Calibrated parameters

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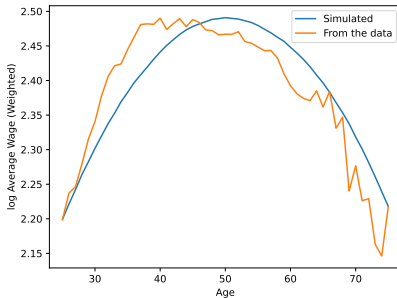
Parameter	Description	Par. Value	Target Moment	Target Value	Model Value
$\alpha$	c utility weight	0.3789	Mean hours worked	33.5	33.48
$\mu_{w_0,\gamma}$	Lab. FE mean	2.1423	Mean wage, $j = 0$	2.1986	2.1992
$\sigma_{w_0,\gamma}$	Lab. FE SD	0.3288	SD wage, $j = 0$	0.2996	0.299
$w_1$	Linear wage coeff.	0.0229	Wage growth	29.16%	29.17%
$w_2$	Quad. wage coeff.	-0.0005	Wage decay	27.32%	27.28%
$w_H$	Health wage coeff.	0.0562	Healthy wage premium	5.13%	5.11%

Table: Calibrated parameters 1

# Targeted hours and wage fit



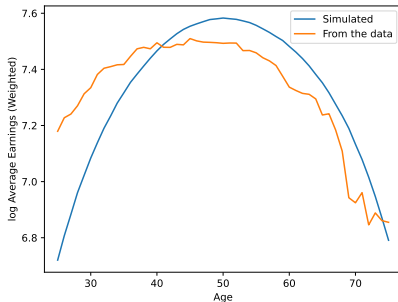
(a) Mean log hours worked (labor)



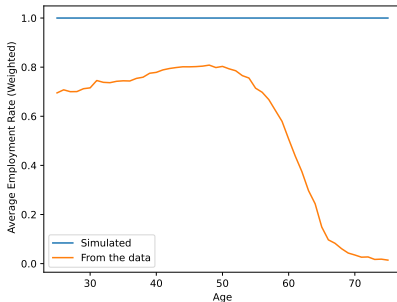
(b) Mean log wage

- Unsurprisingly targeted moments fit pretty well.

# Labor earnings and employment



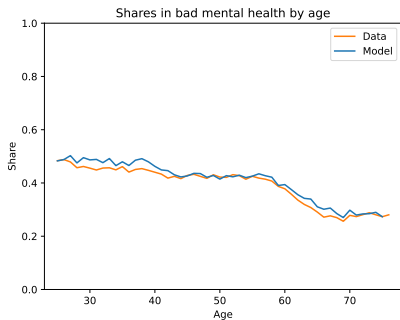
(c) Monthly mean earnings



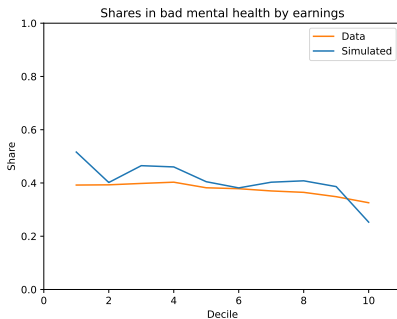
(d) Employment rate

- Earning fit is not great since I entirely miss the extensive margin.

# Shares in bad mental health



(e) Bad MH by age



(f) Bad MH by earnings

# Earnings by health

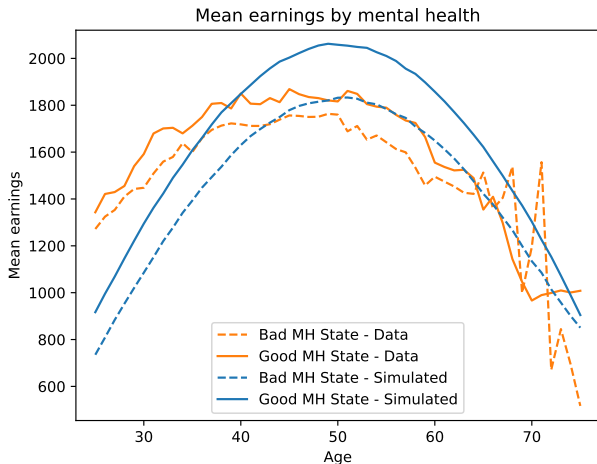
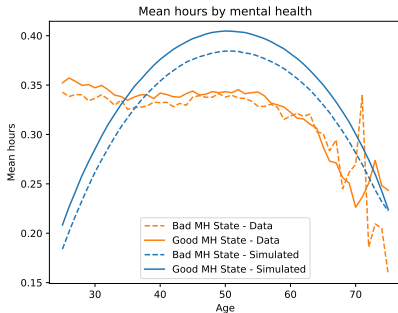


Figure: Mean earnings by mental health

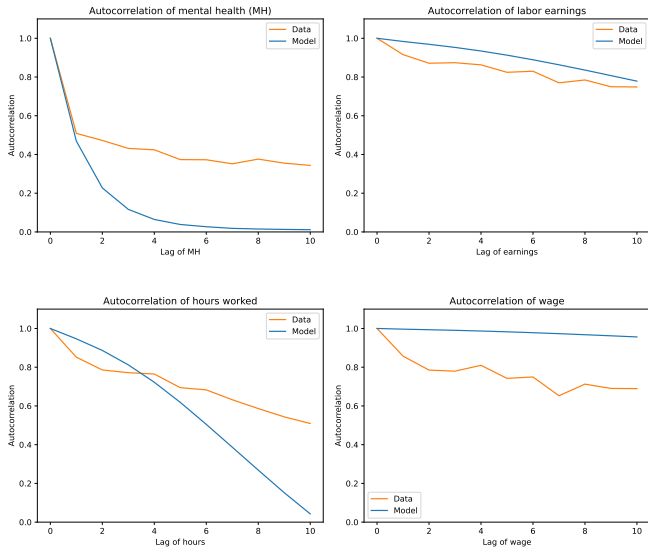
- My health states are more different than the data conditional on employment



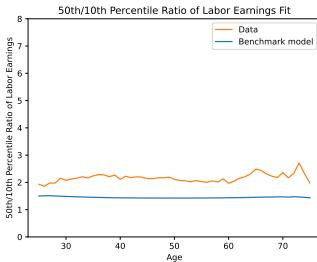
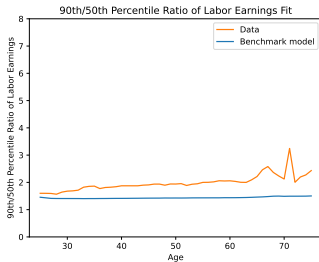
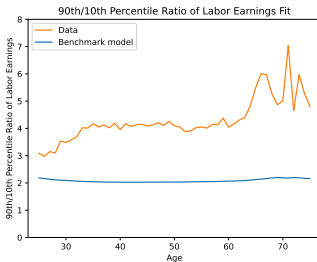
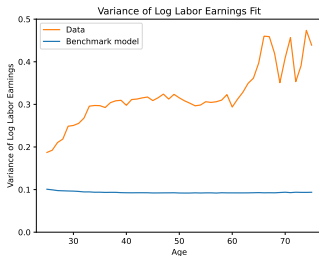
# Wages and hours by health



# Fit persistence



# Fit inequality in log earnings



# Roadmap

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# Counterfactuals

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Consider a counterfactual where we turn off the mental health channel

- Set  $w_H = 0$ . Since MH only effects wages, all mental health channels are turned off.

# Variance of log earnings current counterfactuals

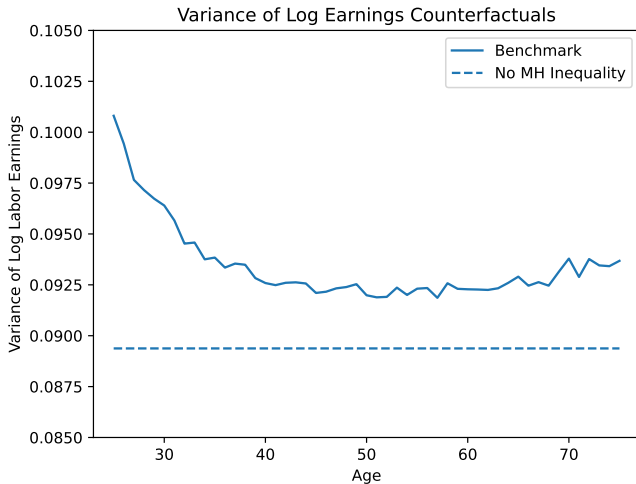
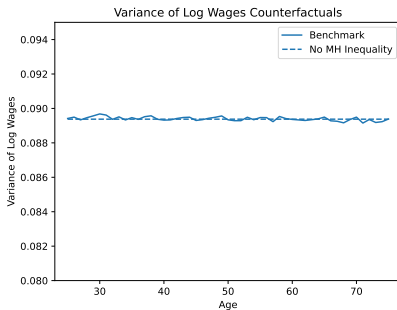
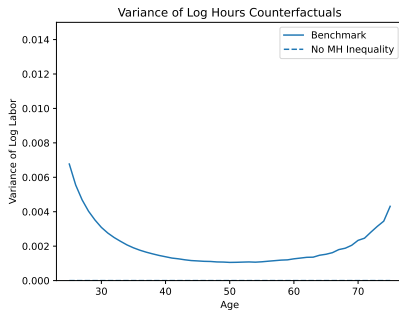


Figure: Variance of log earnings counterfactuals

# Decomposing the variance of log earnings



# Lifetime earnings

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Define annualized lifetime earnings in the model as in Guvenen et al. (2022)

$$\bar{Y}^i \equiv \frac{1}{31} \times \sum_{j=25}^{55} Y_j^i = \frac{1}{31} \times \sum_{j=25}^{55} n_j * z_j$$

Lifetime Earnings Comparison									
Source	Summary		Percentiles					Ratios	
	Mean	Std. Dev.	P10	P25	P50	P75	P90	P90/P10	P50/P10
Baseline Model	19.35	5.94	13.25	17.61	17.77	35.22	40.24	3.04	2.26
No MH Inequality	19.37	5.94	13.34	17.11	17.11	34.22	37.98	2.85	2.22

**Table:** Lifetime earnings statistics



## Lifetime earnings in the data

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Define annualized lifetime earnings in the data as

$$\bar{Y} \equiv \frac{1}{31} \times \sum_{j=25}^{55} \bar{Y}_j$$

where  $\bar{Y}_j = \sum_{i=1}^I Y_j^i$  . Similarly we could define an annualized X percentile as

$$P^x \equiv \frac{1}{31} \times \sum_{j=25}^{55} P_j^x$$

where  $P_j^x$  is the percentile at that age. And could do the same thing in the model... this would give comparable statistics for both.

## Conclusion and next steps

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- Developed a simple lifecycle model with mental health
- Matches some important moments, misses others
- Previewed some results
- Mechanical next steps
  - Match the extensive margin employment and retirement
- More interesting but later..
  - Endogenize mental health (e.g. treatment decisions)
  - Add physical health. How does it effect mental health and vice versa?
  - Are my symptoms caused by stress?

# Thank You!

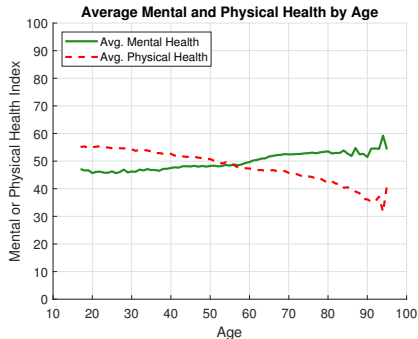
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**Thank you!**

Any questions? I appreciate your feedback!

# Mean Health Over the Lifecycle

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- Index is standardized to a 50 pt. mean and 10 pt. standard deviation
- MH increases by about 1 std. dev., while PH decreases by about 1.5 std. dev. from 25-75

## References

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Abramson, Boaz, Job Boerma, and Aleh Tsyvinski (Apr. 11, 2024). *Macroeconomics of Mental Health*. DOI: 10.2139/ssrn.4793015. URL: <https://papers.ssrn.com/abstract=4793015> (visited on 04/17/2024). Pre-published.



Biasi, Barbara, Michael S. Dahl, and Petra Moser (July 1, 2021). *Career Effects of Mental Health*. URL: <https://papers.ssrn.com/abstract=3889138> (visited on 12/07/2023). Pre-published.



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://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=161035389&site=ehost-live&scope=site> (visited on 11/29/2023).