# Mental Health and the Early Career Dynamics of Young Men

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# This Paper

- Mental health disorders (e.g. depression, anxiety) are highly prevalent early in life:
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    - Our data: $\sim$60% experience poor health by age 40

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- Research Question: How do mental and physical health dynamics shape schooling, work, and early careers of young men?
- Identification challenge: Reverse causality between health and schooling/work.
- Develop and estimate a lifecycle, dynamic discrete choice model with
    - Endogenous health, school/work, and income
    - Unobserved heterogeneity

# Data: Household, Income, and Labor Dynamics in Australia (HILDA)

- Nationally representative annual panel of ~17,000 Australians (cf. PSID).
- Sample: ~2,300 young men after high school graduation, 2002–2021. Cleaning
- Health: Clinically validated SF-36 (Ware & Sherbourne, 1992)
  1. Mental Health: MHI-5 MHI-5
  2. Physical Health: SF-36 physical component score SF36
- Binary health indicators: Cutoff Distribution

$$\widetilde{h}_t = \mathbb{1}[h_t \geq c_h], \;\; h \in \{mh, ph\}$$

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1. Consider starting at age 15 or at least including HS drop-outs
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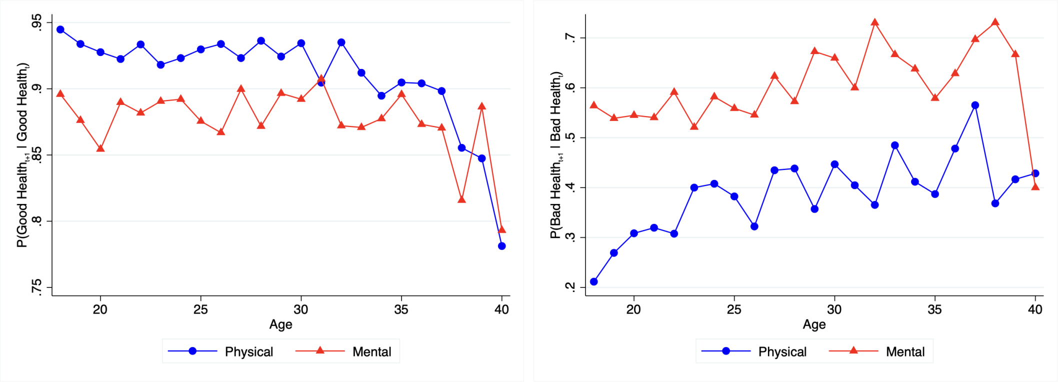
   - have continuous health measures
   - early RF work showing big, negative labor force consequences of poor MH focuses on more severe cases.
   - recent growth in mental distress rates is nearly entirely mild/moderate depression and anxiety, where we would expect weaker labor market effects

# Health is Persistent




(a) P(Good Health$_{t+1}$|Good Health$_t$) (b) P(Bad Health$_{t+1}$|Bad Health$_t$)

Especially, persistence of bad health rises with age.

# Health → Schooling & Work

| | | Time $t+1$ | | | |
|---|---|---|---|---|---|
| *Poor MH* | | Schooling | Full-Time | Part-Time | Not Working |
| Time $t$ | Schooling | 71.66 | 9.31 | 10.12 | 8.91 |
| | Full-Time | 0.00 | 85.81 | 9.37 | 4.82 |
| | Part-Time | 0.00 | 32.10 | 52.84 | 15.06 |
| | Not Working | 0.00 | 5.05 | 22.87 | 72.07 |
| *Good MH* | | Schooling | Full-Time | Part-Time | Not Working |
| Time $t$ | Schooling | 77.13 | 10.04 | 9.16 | 3.68 |
| | Full-Time | 0.00 | 92.44 | 5.80 | 1.76 |
| | Part-Time | 0.00 | 44.35 | 47.93 | 7.72 |
| | Not Working | 0.00 | 11.78 | 39.69 | 48.53 |
| *Poor PH* | | Schooling | Full-Time | Part-Time | Not Working |
| Time $t$ | Schooling | 72.09 | 4.65 | 13.95 | 9.30 |
| | Full-Time | 0.00 | 89.71 | 6.25 | 4.04 |
| | Part-Time | 0.00 | 41.96 | 44.64 | 13.39 |
| | Not Working | 0.00 | 4.97 | 17.68 | 77.35 |
| *Good PH* | | Schooling | Full-Time | Part-Time | Not Working |
| Time $t$ | Schooling | 76.80 | 9.96 | 8.75 | 4.49 |
| | Full-Time | 0.00 | 91.43 | 6.55 | 2.02 |
| | Part-Time | 0.00 | 41.91 | 49.20 | 8.89 |
| | Not Working | 0.00 | 9.79 | 36.73 | 53.48 |

Good health ↑ entry into full-time and ↓ non-employment; part-time is transitory.

# Model Overview

- Life cycle starts at age 18; in each year $t = 1, \ldots, T$ agent knows:
  - Years of education $g_t$
  - Experience $x_t$
  - Mental health $mh_t$
  - Physical health $ph_t$

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  1. School ($m = 1$, up to age 25)
  2. Work full-time ($m = 2$)
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- Wage shock, $\xi_t^m$, determines Consumption, $C_t^m$
- Life shock probability, $P(z_t)$, followed by a health shock, that determines health transition, $\pi_{h,t+1}$.

# Unobserved Heterogeneity and Income

- **Working income** follows Mincer with: Equation

$$y_t^m = f(k_Y, mh_t, ph_t, g_t, x_t) + \xi_t^m, \quad m \in \{2,3\}$$

- **Health transitions** capture: Equation

$$\pi_{h,t+1} = f(k_H, h_t, z_t, d_t^m, y_t^m, g_t), \quad h \in \{mh, ph\}$$

- **Unobserved Heterogeneity**:
    - 2 income ($k_Y \in \{1,2\}$) and 2 health ($k_H \in \{1,2\}$) types, flexibly correlated
    - Driven by family background and initial wealth.

# Flow Utility

- **Flow utility** reflects three main components:

$$U(C_t^m, d_t^m) = u_t^m + \sum_{m=1}^{3} \phi_1^m \cdot \mathbb{1}[a_t \leq 25] \cdot d_t^m + \sum_{m=2}^{3} \phi_2^m \cdot \mathbb{1}[a_t > 25] \cdot d_t^m$$

$$+ \underbrace{\sum_{m=1}^{3} \left[ \phi_{h1}^m \mathbb{1}[mh_t = 1] + \phi_{h2}^m \mathbb{1}[ph_t = 1] \right] \cdot d_t^m}_{\text{Choice-Specific Health Costs}} + \underbrace{\sum_{m=1}^{4} \phi_3^m \mathbb{1}[d_{t-1}^m = d_t^m]}_{\text{Stayers Benefits}} + \varepsilon_t^m$$

$$\text{where} \quad u_t^m = \begin{cases} \psi_1^1 a_t + \psi_2^1 \mathbb{1}[graduate] & \text{if} \quad m = 1 \text{ (School)} \\ \underbrace{log(C_t^m)}_{\text{Risk Aversion}} & \text{if} \quad m = 2, 3, 4 \end{cases} \qquad \text{and} \quad C_t^m = Y_t^m$$

# Optimization Problem and Model Solution

- Each period, agents maximize expected lifetime utility given current state:

Optimization

$$V_t(\boldsymbol{s}_t|k) = \max_{d_t^m} \mathbb{E}\Big[\, U(C_t^m, d_t^m|\boldsymbol{s}_t, k) + \delta V_{t+1}(\boldsymbol{s}_{t+1}|k)\Big]$$

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- Model solved by backward recursion and estimation via Maximum Likelihood.

Identification MLE

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- Kind of important: No UH in U; thus, estimate wage, health, life shock, and UH first. Next, solve DPP and estimate U.

# SUGGESTION 2: Identification Concern #1

Eckstein, Keane, Lifshitz (2019): "In complex dynamic models, it is well known that formal proofs of semiparametric identification are infeasible. So it is standard to rely on heuristic arguments..."

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where $m \in \{2, 3\}$ and $h \in \{mh, ph\}$. UH allows correlation between $\xi$ and $\omega$; and...

- Need instrument z to identify $\partial y / \partial H$

# Life Shock Events

- Leverage life shocks as exogenous variation:

Table: Summary Statistics of Life Shock Events

| | Obs | Mean | Std. Dev |
|---|---|---|---|
| All | 16,667 | 0.257 | 0.437 |
| Death of Friend | 16,667 | 0.058 | 0.233 |
| Victim of Property Crime | 16,667 | 0.049 | 0.216 |
| Victim of Physical Violence | 16,667 | 0.020 | 0.139 |
| Serious Illness of Relative | 16,667 | 0.097 | 0.295 |
| Death of Relative | 16,667 | 0.100 | 0.301 |

*Note*: Life shock event questions are asked annually and are based on the respondents' experience during the past 12 months.

- Life shocks = 1 if any event occurs.

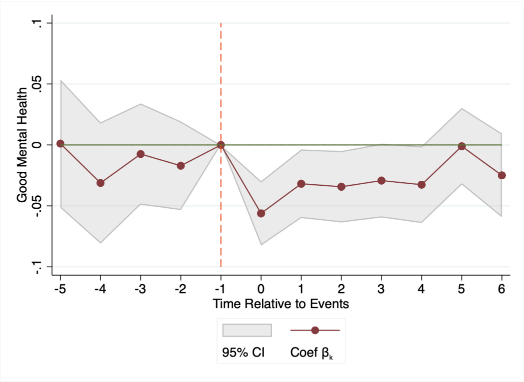
# Addressing Health Endogeneity

- Event-study with staggered treatment (Sun & Abraham 2020)
- Specification:

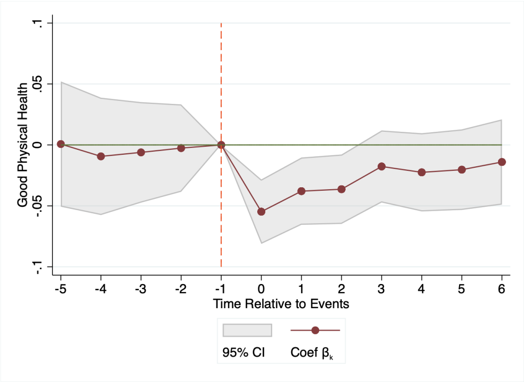
$$y_{gt} = \alpha + \sum_{\substack{k=-5 \\ k \neq -1}}^{6} \beta_k z_{gk} + X'_{gt}\Gamma + \gamma_t + \epsilon_{gt},$$

where $y_{gt}$ is the outcome of individual $g$ in year $t$, controlling for age, education, and including individual-clustered standard errors.

# Event-Study: Life Shocks → Health




(a) Good Mental Health




(b) Good Physical Health

Life shocks have short-term negative impacts on good health.

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- Need not 1 but 2 $z_t$ to separately identify $\partial y/\partial mh$ and $\partial y/\partial ph$.
- Need inst. for $y$ to identify $\partial H/\partial y$ ($x_t$?).
- Endogeneity of $d_t^m$ in $H_{t+1}$ totally unaccounted for (also estimate very large effects).

# SUGGESTION 2: Identification Concern #2

Eckstein, Keane, Lifshitz (2019): "...Our model can be viewed as a dynamic version of Heckman's (1974) labor supply model, but where offer wage functions are combined with a far more elaborate selection mechanism. Intuitively, just as in his static model, identification relies on exclusion restrictions of two types. First, to identify offer wage functions given selection, we need variables that exogenously shift the decision rule for work (e.g., by shifting preferences or values of leisure) but do not enter the offer wage function directly. Second, to identify utility parameters, we need variables that exogenously shift offer wages but do not alter preferences or values of leisure."

# SUGGESTION 2: Identification Concern #2

This perfectly describes an issue here!

Need to allow:

1. Correlation between the wage errors, $\xi_t^m$, and preference errors, $\epsilon_t^m$.
2. Variable that shifts employment choice, but not wages (or health)
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All of this is to say...allow UH to extend to employment/school preferences, add a few ERs, and estimate in one step. (All perfectly feasible)

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  - UH not doing much for you in finding low income type – where is the "bad" type?
  - Full-time work $\uparrow$ Good MH by $\sim$45%, Good PH by $\sim$47%.
- Some sensible magnitudes regarding health and income:
  - An additional \$1,000 in annual income $\uparrow$ Good MH by $\sim$0.2%, Good PH by $\sim$0.1%.
  - Good MH $\uparrow$ FT income by $\sim$3.6%, PT income by $\sim$14.6%
  - Good PH $\uparrow$ FT income by $\sim$3.8%, PT income by $\sim$7.5%

# Counterfactuals

1. Role of Permanent Health Differences
   1. Unobserved health types
   2. Mental vs Physical health
2. Effects of Transitory Shocks
   1. Transitory health shocks: Poor Health
   2. Transitory labor market shocks: Job Loss

   - Shock age 30
   - "Health Spiraling"
3. Resilience to Transitory Shocks
   1. How resilient?

# Simulation Procedure

- Simulate individuals from age 18, each with 100 life-cycle paths.
- Compute Present Discounted Income (PDI of FT, PT, and NW income, with $\delta = 0.95$).
- Compute Change in Consumption Equivalent Variation (CEV) that captures:
  - Welfare beyond income
  - Risk aversion
  - Utility gains

# I.I Permanent Health Types

| | Health Types | | |
|---|---|---|---|
| | Overall | Poor H | Good H |
| PDI | 872307.35 | 821604.38 | 908639.14 |
| PDI (std) | 288323.55 | 300437.86 | 280482.00 |
| PDI (%) | 6.17 | - | 10.59 |
| CEV | 161758.62 | - | 273240.91 |
| CEV (%) | 18.47 | - | 31.19 |
| Years in Schooling | 2.51 | 2.78 | 2.33 |
| Years in Full-Time | 15.65 | 14.92 | 16.17 |
| Years in Part-Time | 3.71 | 3.67 | 3.75 |
| Years Not Working | 2.10 | 2.63 | 1.74 |
| Periods in Good MH | 18.35 | 12.63 | 22.31 |
| Periods in Good PH | 21.10 | 19.32 | 22.36 |

# I.II Mental vs Physical Health

Earnings Inequality

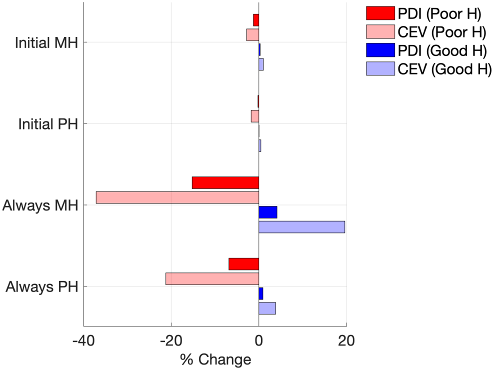


Figure: % Change in PDI and CEV by Health Counterfactual Scenarios Relative to Model

- MH impacts exceed PH; always poor MH cuts PDI and CEV by >20%.

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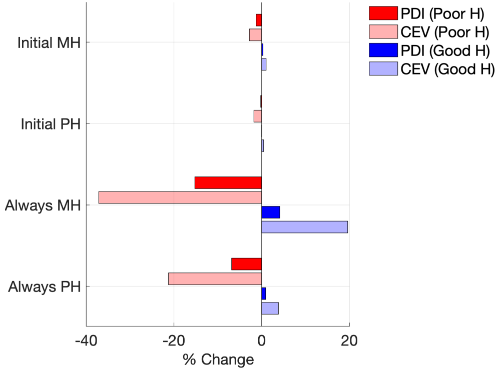



Figure: % Change in PDI and CEV by Health Counterfactual Scenarios Relative to Model

- MH impacts exceed PH; always poor MH cuts PDI and CEV by >20%.
- CPF (2025) calculated annual US WTP for "magic pill."

# II. What Are the Effects of Transitory Shocks at Age 30?

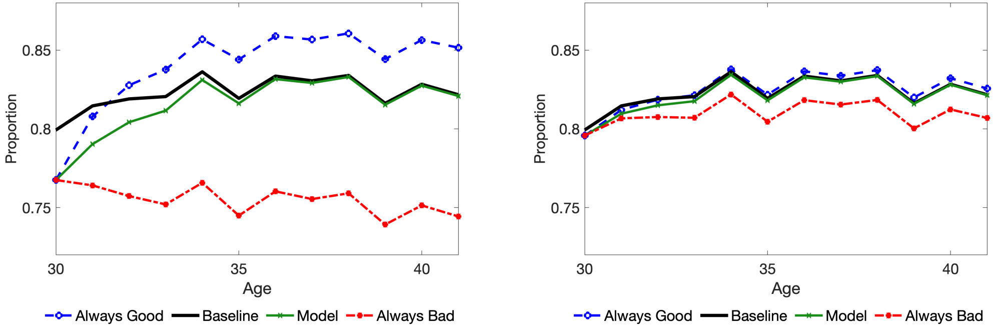
- Assess how transitory shocks affect health $\Leftrightarrow$ labor market outcomes.
- Compare four scenarios:
  1. **Baseline**: No treatment
  2. *Treatment*: Negative shock at age 30
     - **Always Good**: Always in good health
     - **Model**: Health evolves endogenously
     - **Always Bad**: Always in poor health $\longrightarrow$ **'Spiraling'**
- 'Always Good/Bad' serve as bounds for treatment effects.

  $\longrightarrow$ **'Effective Treatment'**

# II.I Transitory Bad Health → Labor Market Outcomes PT, NW Income

Mental Health Shock     Physical Health Shock

Full-Time

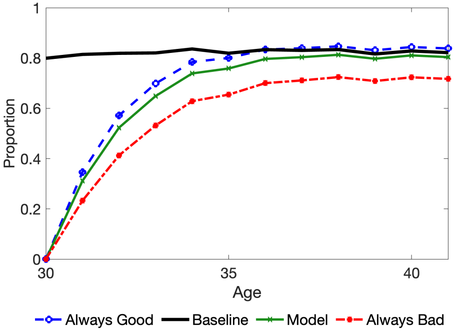


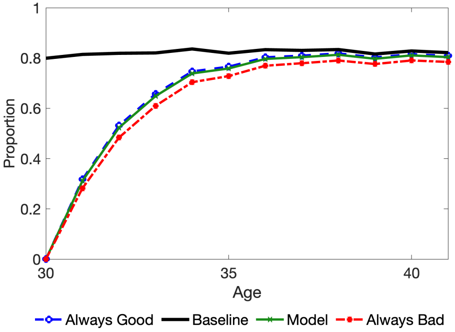

Poor MH shock lowers full-time work and the gap persists.

# II.II Health ← Transitory Labor Shocks (Job Loss) Health PT, NW Income

Mental Health Physical Health

Full-Time




Recovery from job loss is much slower with poor MH.

# III. Are People Resilient and What Are the Effective Treatments?

- We relate to the psychology literature - **Resilience**.

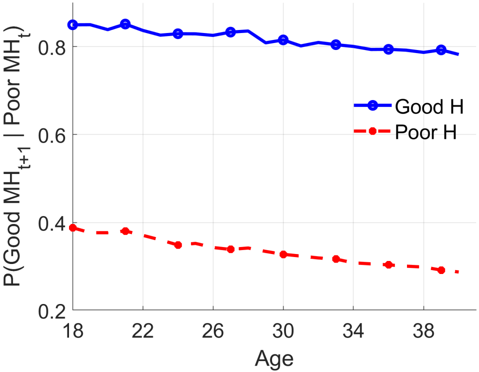
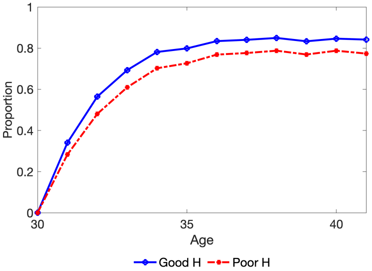



Figure: Resilience by Health Type

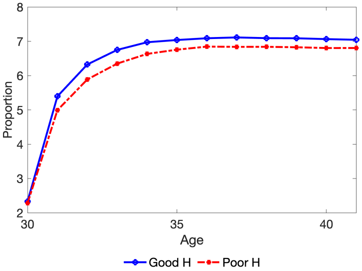
# III.I How Resilient to Transitory Labor Market Shocks? PT, NW

- Conditional on being in full-time employment and good mental health at age 29, what is the effect of job loss at age 30?

(a) Full-Time Employment




(b) Log(Weekly Income)



# SUGGESTION 3: A thought...

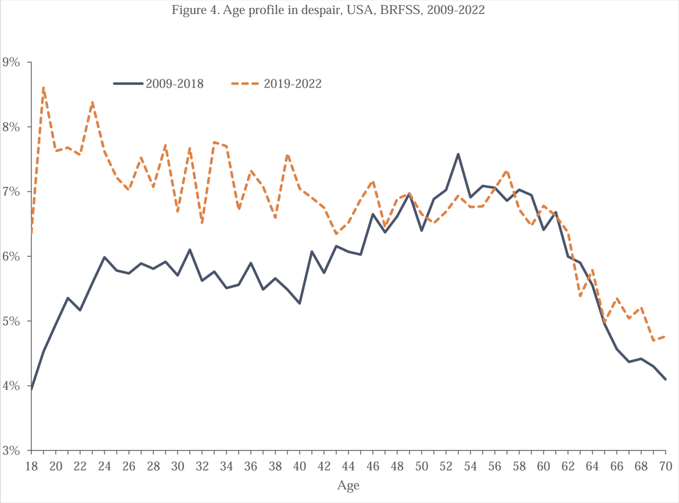



Figure: Blanchflower, Bryson, Xu (2024)

# Conclusion and Next Steps

- Mental and physical health are persistent.
- Life shocks adversely affect health in the short-run.
- Mental health has stronger effects, relative to physical health, on labor supply at the extensive margin.
- Counterfactuals:
  - Permanent types matter $\longrightarrow$ Resilience
  - Transitory health shocks reduce labor supply more than unemployment shocks.
  - Mental health amplifies earnings inequality.
  - Further examine treatment effects and quantify welfare losses
- Poor mental health leaves deeper scars relative to physical health
  $\longrightarrow$ Early interventions can reduce inequality and raise productivity.

Thank you!

# Related Literature back

1. Health and education
   - e.g. Cornaglia, Crivellaro, and McNally (2015); Rodwell et al. (2017)
2. Health and labor market outcomes
   - Mental health: Kouzis and Eaton (1994); Kessler and Frank (1997); Chatterji et al. (2007); Frijters et al. (2014); Wang et al. (2023)
   - Physical health: Haan and Myck (2009); Lenhart (2019)
   - Both dimensions: Ettner (2000); Ohrnberger et al. (2017); Lundborg et al. (2014)
3. Dynamic structural models of health
   - Elderly: French (2005); De Nardi, Pashchenko, and Porapakkarm (2025)
   - Working-age: Papageorge (2016); Capatina, Keane, and Maruyama (2018); Capatina and Keane (2023); Jolivet and Postel-Vinay (2024); Hosseini, Kopecky, and Zhao (2021) Cronin (2025)
   - Mental and/or physical health: Cozzi, Mantovan, and Sauer (2024); Drozd (2025)

# Mental Health Inventory (MHI-5) back

How much of the time during the last 4 weeks,

1. Have you been a nervous person?
2. Have you felt so down in the dumps that nothing can cheer you up?
3. Have you felt calm and peaceful?
4. Have you felt down?
5. Have you been a happy person?

The score is from 1 (All the time) to 6 (None of the time) and recoded and rescaled to 0-100 such that a high score implies better mental health.

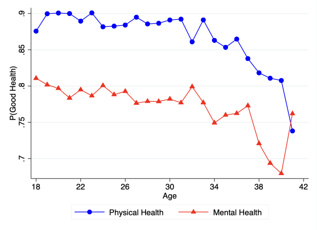
# SF-36 Physical Component Score (PCS)

- SF-36 is categorized into 8 main scales: Physical functioning (PF), role physical (RP), bodily pain (BP), general health (GH), vitality (VT), social functioning (SF), role emotional (RE), and mental health (MH).
- We follow the standard scoring guidelines outlined by Ware Jr (2000), which aggregate the PH domains into standardized summary score.
- We transform into z-scores using Australian population norms, apply Australian factor-scoring coefficients to obtain the PCS, and rescale to the norm-based T-metric (mean 50, SD 10).
- We use 40, which is one standard deviation below the mean, as our cutoff for poor physical health.

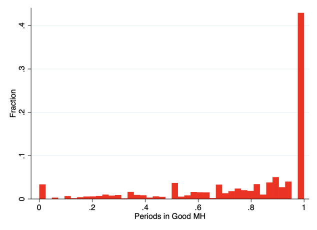
# SF-36 Example Question - Role Physical back

- e.g. (RP) During the past 4 weeks, have you had any of the following problems with your work or other regular daily activities as a result of your physical health?
  1. Cut down the amount of time you spent on work or other activities
  2. Accomplished less than you would like
  3. Were limited in the kind of work or other activities
  4. Had difficulty performing the work or other activities (for example, it took extra effort)

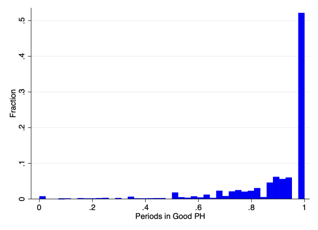
# Health Over the Life-Cycle back




(a) Health Over the Life-Cycle




(b) Good Mental Health




(c) Good Physical Health

# Timeline back

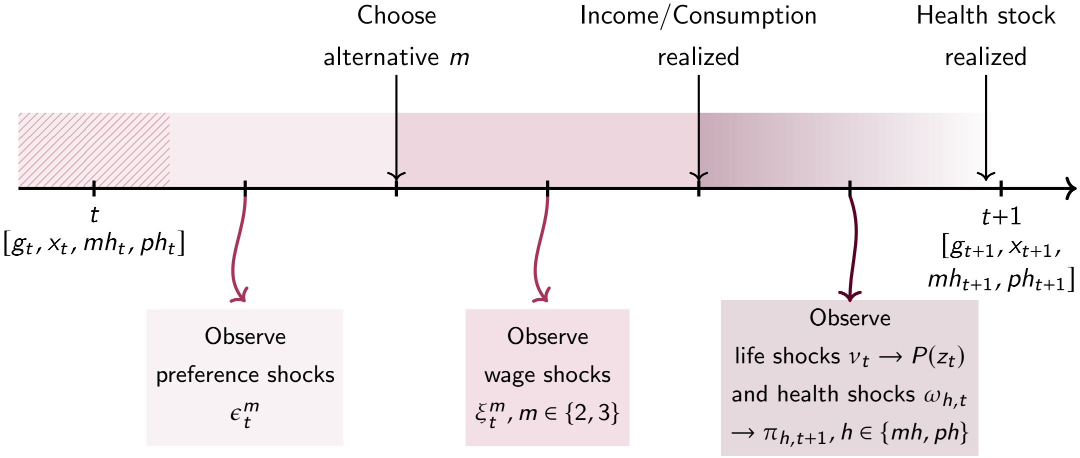



Figure: Model Timeline

# Weekly Income back

- Working income is a function of health and demographics:

$$y_t^m = \rho_y^m \cdot \omega_{k_Y}^Y + \psi_1^m a_t + \psi_2^m (a_t)^2/100 + \psi_3^m g_t + \psi_4^m x_t + \psi_5^m (x_t)^2/100 + \psi_{h1}^m \mathbb{1}[mh_t = 1] + \psi_{h2}^m \mathbb{1}[ph_t = 1] + \xi_t^m, \quad k \in \{1,2\}, m \in \{2,3\} \tag{1}$$

where $\xi_t^m \overset{iid}{\sim} N(0, \sigma^2_{\xi^m}), m \in \{2,3\}$.

- Not working income depends on age and probability of receiving government allowance:

$$y_t^4 = \begin{cases} \psi_0^4 + \psi_1^4 a_t + \psi_2^4 (a_t)^2/100 + \xi_t^4 & \text{with prob } p_g^4 \\ 0 & \text{with prob } 1 - p_g^4 \end{cases} \tag{2}$$

# Health Probabilities back

- Health and life event shocks follow T1EV.
- Specification:

$$
\pi^{i,i'}_{h,t+1}(d^m_t, \boldsymbol{s}_t | k_H, z_t) = \frac{exp\big[A_h\big]}{1 + exp\big[A_h\big]},
$$

$$
\begin{aligned}
\text{where} \quad A_h &= \rho_h \cdot \omega^H_{k_H} + \alpha_{h,1} h_t + \alpha_{h,2} z_t + \alpha_{h,3} g_t + \alpha_{h,4} a_t + \alpha_{h,5} (a_t)^2/100 \\
&+ \sum_{m=1}^{3} \alpha^m_{h,6} \cdot d^m_t + \alpha_{h,7} \sum_{m=2}^{4} Y^m_t \cdot d^m_t + \alpha_{h,8} a_t \cdot d^1_t, \\
& k_H \in \{1, 2\}, h \in \{mh, ph\}
\end{aligned} \tag{3}
$$

- Life shock probabilities simply depend on age and age squared.

# Optimization Problem

- In each period, agents maximize the expected present value of lifetime utility, given current state:

$$V_t(\boldsymbol{s}_t) = \max_{d_t^m} \underbrace{\mathbb{E}_{\boldsymbol{\xi}_t}\mathbb{E}_{\eta_t}\mathbb{E}_{\nu_{h,t}} U(C_t^m, d_t^m) + \delta \mathbb{E}_{\boldsymbol{\xi}_{t+1}}\mathbb{E}_{\eta_{t+1}}\mathbb{E}_{\nu_{h,t+1}}\mathbb{E}_{\boldsymbol{\varepsilon}_{t+1}} V_{t+1}(\boldsymbol{s}_{t+1})}_{\Omega(C_t^m, d_t^m, \boldsymbol{s}_t)} \tag{4}$$

$$\text{s.t.} \quad C_t^m = Y_t^m$$

where

$$\begin{aligned}
\bar{\Omega}(C_t^m, d_t^m, \boldsymbol{s}_t) &= U(C_t^m, d_t^m) \\
&+ \delta \cdot p(z_t) \cdot \sum_{i'=0}^{1}\sum_{j'=0}^{1} \left[\pi_{mh,t+1}^{i,i'}(mh_t, \boldsymbol{s}_t | z_t = 1) \cdot \pi_{ph,t+1}^{j,j'}(ph_t, \boldsymbol{s}_t | z_t = 1) \cdot \mathbb{E} V_{t+1}(\boldsymbol{s}_{t+1})\right] \\
&+ \delta \cdot (1 - p(z_t)) \cdot \sum_{i'=0}^{1}\sum_{j'=0}^{1} \left[\pi_{mh,t+1}^{i,i'}(mh_t, \boldsymbol{s}_t | z_t = 0) \cdot \pi_{ph,t+1}^{j,j'}(ph_t, \boldsymbol{s}_t | k, z_t = 0) \cdot \mathbb{E} V_{t+1}(\boldsymbol{s}_{t+1})\right]
\end{aligned} \tag{5}$$

## Optimization Problem back

- Since $\varepsilon_t^m \sim T1EV$, the probability of choosing alternative $m$ is:

$$p(d_t^m = 1|\boldsymbol{s}_t) = \frac{exp(\widetilde{\Omega}(C_t^m, d_t^m))/\sigma_\varepsilon)}{\sum_{m=1}^{4} exp(\widetilde{\Omega}(C_t^m, d_t^m)/\sigma_\varepsilon)} \tag{6}$$

where $\Omega(C_t^m, d_t^m) = \widetilde{\Omega}(C_t^m, d_t^m)) + \varepsilon_t^m$. Following Rust (1987), the expected value function can be written as

$$\begin{aligned} \mathbb{E}[V_{t+1}(s_{t+1})|\boldsymbol{s}_t] &= \mathbb{E}_{\boldsymbol{\varepsilon}_t} \max_{d_t^m} \sum_{m=1}^{4} \left[\widetilde{\Omega}(C_t^m, d_t^m) + \varepsilon_t^m\right] \\ &= \sigma_\varepsilon log\left(\sum_{m=1}^{4} exp\left(\frac{\widetilde{\Omega}(C_t^m, d_t^m)}{\sigma_\varepsilon}\right)\right) + \sigma_\varepsilon \gamma \end{aligned} \tag{7}$$

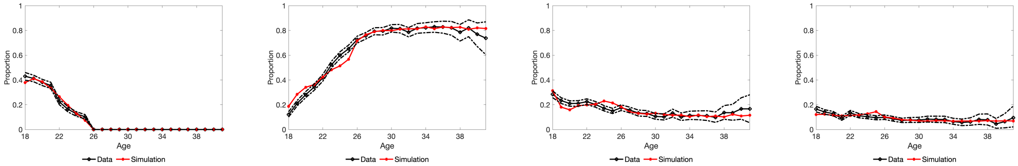
# Sketch of Identification back

- All parameters are identified through variation in the data:
  - Utility parameters:
    - Risk aversion $\mu$: consumption under income volatility
    - Utility costs $\phi^m$: choices across schooling, part-/full-time, not working
    - Health costs $\phi^m_h$: differences in MH/PH outcomes
    - Switching costs $\phi^m_3$: persistence vs. switching in choices
  - Income parameters:
    - Health effects $\psi^2_h$: income variation of workers in poor health
    - Remaining $\psi$: age, education, experience, and choice variation
  - Unobserved heterogeneity:
    - Types: 2 income ($k_Y$), 2 health ($k_H$)
    - Correlation: joint probabilities $p(k_Y, k_H)$
    - Identified by differential impact of health on income not explained by observables

# MLE back

$$
\begin{aligned}
&\mathcal{L}_n(\Theta|k) = \prod_{i=0}^{1} p(mh_{t_1} = i|k)^{\mathbb{1}[mh_{n,t_1}=i]} \cdot \prod_{j=0}^{1} p(ph_{t_1} = j|k)^{\mathbb{1}[ph_{n,t_1}=j]} \\
&\cdot \prod_{\tau=1}^{T_n-1} \prod_{m=1}^{4} \Bigg[ P(d_\tau^m = 1|\boldsymbol{s}_t, k) \cdot \widetilde{f}(y_\tau^m|k_Y) \\
&\cdot \Bigg[ P(z_\tau)^{\mathbb{1}[z_{n,\tau}=1]} \cdot \Bigg[ \prod_{l'=0}^{1} \pi_{mh,\tau+1}^{l,l'}(mh_\tau, \boldsymbol{s}_t|k, z_t = 1)^{\mathbb{1}[mh_{n,\tau+1}=l']} \cdot \prod_{q'=0}^{1} \pi_{ph,\tau+1}^{q,q'}(ph_\tau, \boldsymbol{s}_t|k, z_t = 1)^{\mathbb{1}[ph_{n,\tau+1}=q']} \Bigg] \\
&\cdot (1 - P(z_\tau))^{\mathbb{1}[z_{n,\tau}=0]} \cdot \Bigg[ \prod_{l'=0}^{1} \pi_{mh,\tau+1}^{l,l'}(mh_\tau, \boldsymbol{s}_t|k, z_t = 0)^{\mathbb{1}[mh_{n,\tau+1}=l']} \cdot \prod_{q'=0}^{1} \pi_{ph,\tau+1}^{q,q'}(ph_\tau, \boldsymbol{s}_t|k, z_t = 0)^{\mathbb{1}[ph_{n,\tau+1}=q']} \Bigg] \Bigg] \Bigg]^{\mathbb{1}} \\
&\cdot \prod_{m=1}^{4} \Bigg[ P(d_{T_n}^m = 1|\boldsymbol{s}_{T_n-1}, k) \cdot \widetilde{f}(y_{T_n}^m|k_Y) \Bigg]^{\mathbb{1}[d_{n,T_n}^m=1|k]}
\end{aligned} \tag{8}
$$

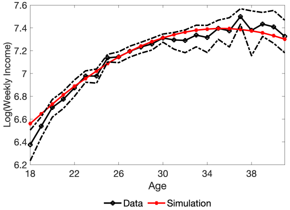
# Model Fit - Life-Cycle Choices



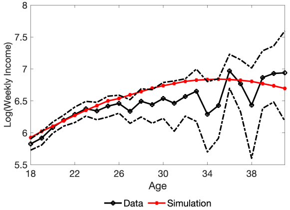

(a) Schooling (b) Full-Time (c) Part-Time (d) Not Working

*Note*: The dotted lines correspond to the 95% confidence interval around the data, calculated using 1,000 bootstrapped data sub-samples. We take the initial states of data individuals as given $\mathbf{s}_1$ and simulate their choices forward using the model 1,000 times.

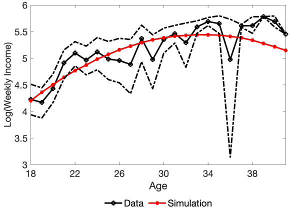
# Model Fit - Income




(a) Full-Time



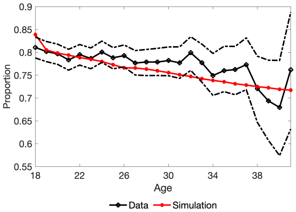

(b) Part-Time



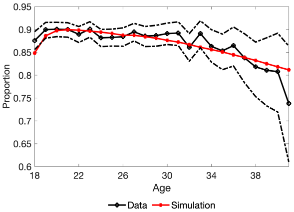

(c) Not Working

*Note*: The dotted lines correspond to the 95% confidence interval around the data, calculated using 1,000 bootstrapped data sub-samples. We take the initial states of data individuals as given $\mathbf{s}_1$ and simulate forward the income using the model 1,000 times.

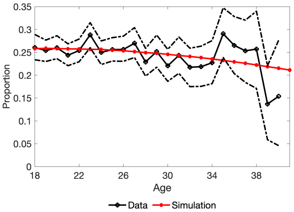
# Model Fit - Health and Life Shocks back




(a) Mental Health



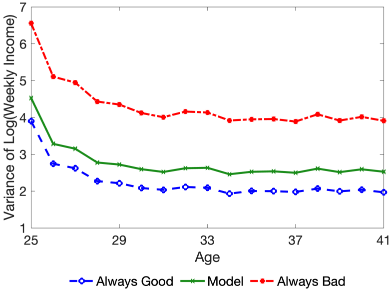

(b) Physical Health



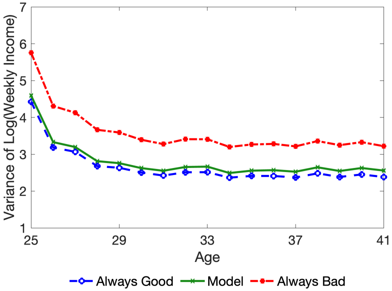

(c) Life Shocks

*Note*: The dotted lines correspond to the 95% confidence interval around the data, calculated using 1,000 bootstrapped data sub-samples. We take the initial states of data individuals as given $\mathbf{s}_1$ and simulate forward using the model 1,000 times.

# I.II Health on Earnings Inequality back




(a) By Mental Health



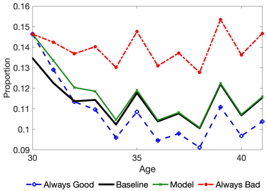

(b) By Physical Health

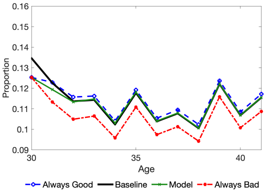
Figure: Variance of Log of Weekly Income Over the Life-Cycle

# II.I Transitory Bad Health → Labor Market Outcomes back

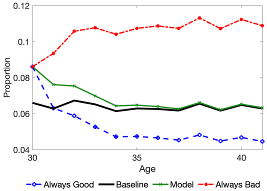
Mental Health Shock Physical Health Shock

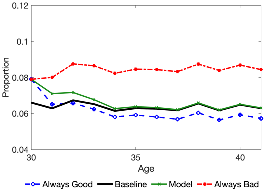
## Part-Time




## Not Working

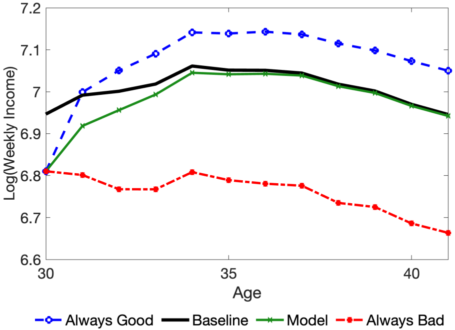


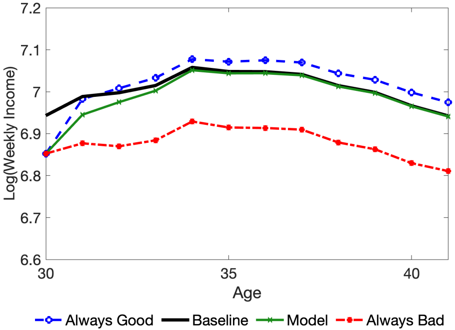



# II.I Transitory Bad Health → Labor Market Outcomes back

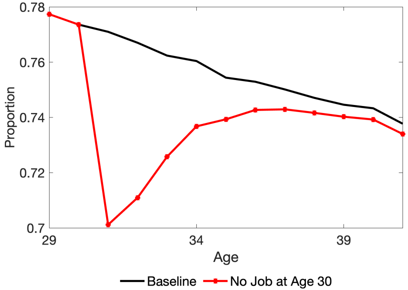
Mental Health Shock     Physical Health Shock

Weekly Income

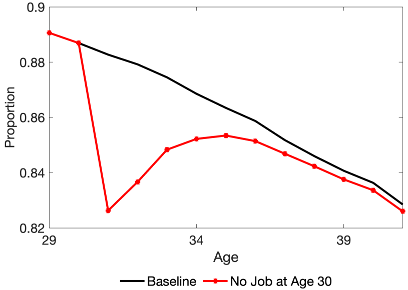


# II.II Health ← Transitory Labor Market Shocks (Job Loss) back




(a) Mental Health



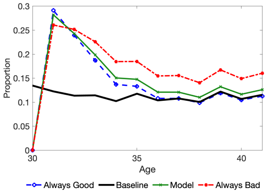

(b) Physical Health

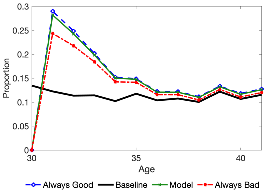
Figure: Effect of Unemployment at Age 30 on Health

# II.II Health ← Transitory Labor Market Shocks (Job Loss) back

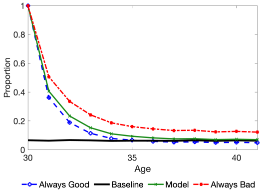
Mental Health Physical Health

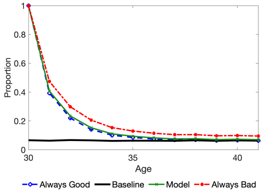
Part-Time




Not Working

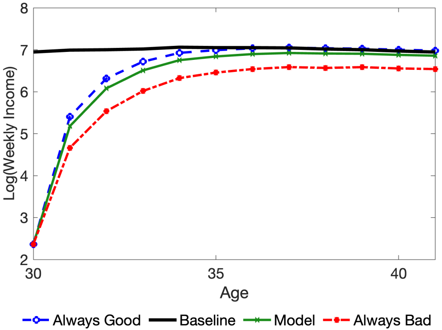


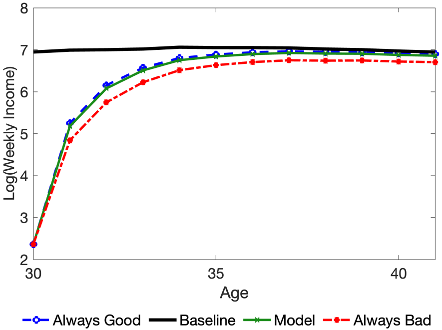



# II.II Health ← Transitory Labor Shocks (Job Loss) back

Mental Health     Physical Health

Weekly Income

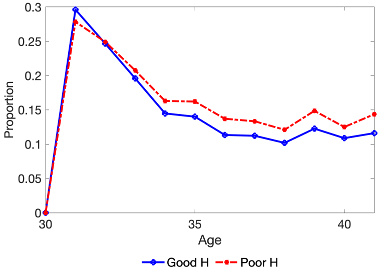


# III.I How Resilient to Transitory Labor Market Shocks? back

- Conditional on being in full-time employment and good mental health at age 29, what is the effect of job loss at age 30?

(a) Part-Time Employment




(b) Not Working