Mental Health and the Early Career Dynamics of Young Men*

Preliminary and Incomplete

Cecilia S. Diaz-Campo, Barton H. Hamilton, and Martin Luccioni

Olin Business School
Washington University in St. Louis

Hyun Soo Suh

Department of Economics
Washington University in St. Louis

Updated: June 1, 2025

Abstract

Mental and physical health are persistent and highly correlated, yet existing literature focuses on one dimension or combines them into a single measure, overlooking their dynamic relationship. This paper endogenizes both mental and physical health, exploring how these health dynamics influence schooling and occupational choices for young men. Using data from the Household Income and Labour Dynamics in Australia (HILDA), we first document the life-cycle patterns of mental and physical health and examine the two-way interactions between health and decision-making processes, leveraging life shock events as instruments. We then build a discrete choice dynamic programming model with unobserved heterogeneity allowing correlation between health and income. Our estimates and counterfactual exercises show that mental health plays a central role in shaping earnings, utility, and long-run outcomes. It contributes more to utility and drives greater inequality to present discounted income than physical health. By jointly modeling both dimensions, we are able to isolate their distinct effects on occupational sorting and income dynamics.

Keywords: Mental health, physical health, occupational choice, structural models

JEL Classification: I10, J21, J24

*First version: June 1, 2025. We thank seminar participants at WUSTL Olin Brown Bag Series. All errors are our own.

Electronic addresses: cdiazcampo@wustl.edu, hamiltonb@wustl.edu, luccioni@wustl.edu, hyunsoo@wustl.edu

1 Introduction

Since Grossman (1972)'s seminal work, health has been recognized as a crucial component of human capital, shaping outcomes across the life cycle—from childhood,[1] adolescence,[2] to adulthood.[3] In particular, past research has documented positive relationships between either mental or physical health and educational and labor market outcomes.[4] Despite these potential distinct effects, the literature often treats health as a single dimension or focuses on one aspect. However, mental and physical health may evolve differently and may have interacting effects on behavior and outcomes across the life cycle.

In this paper, we explore how the dynamics of mental and physical health influence schooling and employment decisions (and vice versa), and, ultimately, the early career trajectories of young men. We develop a dynamic discrete choice model of schooling, employment, and earnings with endogenous mental and physical health and unobserved heterogeneity. The framework allows us to assess the importance of different pathways through which mental and physical health impact human capital accumulation, productivity, and pay: (1) Permanent health differences may be correlated with permanent productivity differences (De Nardi, Pashchenko, and Porapakkarm, 2025); (2) Negative health shocks may reduce labor force participation, impacting human capital accumulation over the life-cycle; (3) Health shocks may directly impact worker productivity; (4) Labor market shocks may impact mental and physical well-being, exacerbating the long-term impacts of losing a job or experiencing a reduction in pay. We estimate the impact of each of these mechanisms, separately assessing the impacts of mental and physical health.

In our model, agents are risk-averse and make decisions on consumption, schooling, and employment under uncertainty regarding their future health status, life shock events, income, and preferences. We model future mental and physical health as functions of current health, life shocks, demographics, employment, and income, which in turn influence agents' utility and income. Given the interdependent and persistent nature of health, including life shocks is crucial because they may have immediate adverse effects and potentially disrupt individuals' optimal long-term paths, thereby influencing their choices and income.

We use rich panel data from the Household Income and Labour Dynamics in Australia (HILDA) survey to estimate the model. The database includes multiple measures of mental and physical health, which we use to define health-state spaces over time. To address the endogeneity bias from reverse causality between employment and health, we exploit real-life shocks (e.g., the death of a friend or relative, serious illness of a relative, victimization from physical violence, and property crime) as instruments and show that current health and employment choices significantly

[1] See e.g., Currie and Stabile (2006); Fletcher and Wolfe (2008).

[2] See e.g., Fergusson and Woodward (2002); Fletcher (2008, 2010, 2013).

[3] See e.g., French (2005); French and Jones (2011); De Nardi, French, and Jones (2010); De Nardi, Pashchenko, and Porapakkarm (2025).

[4] Some include Ettner et al. (1997); Cornaglia et al. (2015); Rodwell et al. (2018); Lenhart (2019).

affect future health outcomes.

We estimate the model in two stages. In the first stage, we jointly estimate the working income process, initial mental and physical health, as well as mental and physical health transitions, allowing for unobserved heterogeneity in health and income types across individuals. This approach enables us to account for selection into employment and individual-specific differences that may otherwise bias the estimated income processes. In the second stage, we use the first stage estimates to internally recover the utility parameters.

Our structural estimates indicate that individuals are risk-averse and derive non-pecuniary benefits from schooling and employment, compared to remaining unemployed. Moreover, we capture higher occupational persistence in schooling and not working more than in working. Health plays a central role in shaping utility, with substantial heterogeneity across dimensions and occupations. Mental health, in particular, has a much stronger effect on utility than physical health, even conditional on occupation, with the largest gap observed among non-working individuals. This pattern points to a potential vicious cycle in which poor mental health lowers utility from all occupations, especially unemployment, further discouraging labor market participation or schooling. By jointly modeling mental and physical health, we are able to disentangle their distinct roles and show that mental health is a key driver of utility and occupational choice across the life cycle.

With our estimated model, we conduct three main counterfactual analyses. First, we examine the effect of unobserved latent types and health status on present discounted income. We find large differences between the high-income and good-health type, who earn more than twice as much as those in the low-income and poor-health type. This shows how unobserved health and income types correlated together shape long-run earnings. Second, we compare the percentage differences in present discounted income and show that mental health increases inequality more than physical health—about 3% higher on average. These differences are larger in the bottom income percentiles, where poor mental health leads to steeper income losses. Lastly, we study the effect of unemployment on health and find that job loss has large and persistent negative effects, especially on mental health. A job loss at age 30 causes a sharp drop in mental health with a slower recovery compared to physical health. Overall, these exercises highlight the two-way interactions between health and labor market outcomes and provide a direct comparison between mental and physical health in shaping inequality and life-cycle trajectories.

Our paper primarily contributes to two main literature in health and structural labor. First, we further explore the impact of health on schooling and labor market outcomes. Cornaglia et al. (2015) and Rodwell et al. (2018) document a link between poor mental health and increased dropout rates and 'not in education, employment, or training' (NEET) status. Similarly, poor mental health is linked to lower employment probabilities, reduced earnings, and fewer work hours (Kessler and Frank, 1997; Frank and Gertler, 1991; Kouzis and Eaton, 1994; Hamilton et al., 1997; Wang, Frank, and Glied, 2023; Biasi, Dahl, and Moser, 2021), and adverse labor market outcomes can negatively affect mental well-being (Linn et al., 1985; Alexandre and French, 2001; Friedland and Price, 2003; McKee-Ryan et al., 2005; Paul and Moser, 2009; Peng, Meyerhoefer, and Zuvekas, 2013). Among studies that explore the joint impact of mental and physical health on labor market outcomes, researchers have identified a significant interdependence (Ettner, 2000; Ohrnberger et al., 2017). For instance, Lundborg, Nilsson, and Rooth (2014) find a strong relationship between health at age 18 and adult earnings, where mental health has greater effects than physical health. Haan and Myck (2009) examine labor market risks with unobserved heterogeneity and find that the probability of joblessness increases with poor health and vice versa. We extend the literature and are the first to incorporate both mental and physical health states as endogenous factors within a life-cycle structural framework.

We also add to the rich literature using an instrumental variables approach to address endogeneity bias of health. For instance, Ettner et al. (1997) use childhood and family psychiatric disorders and Chatterji et al. (2007) use parental psychological illness to control for selection and find negative associations with labor force participation and conditional income. Using HILDA, Frijters et al. (2014) use the death of a close friend to control for mental health shocks and show that one standard deviation decline in mental health reduces employment by 30 percentage points. Similar to their study, we use life shock events as sudden health shocks, which can lead to substantial and lasting declines in earnings due to increased health costs and decreased productivity (Lenhart, 2019).

Second, our paper contributes to the literature on dynamic structural models related to health. Based on an elderly population, French (2005); French and Jones (2011); De Nardi, French, and Jones (2010) examine the effect of health on retirement decisions in a life-cycle model setting, and Jacobs and Piyapromdee (2016) study the reverse retirement behavior. De Nardi, Pashchenko, and Porapakkarm (2025) explore the correlation between health types and fixed characteristics such as patience and their long-term consequences on earnings and welfare. In the context of Germany, Mahler and Yum (2023) quantify the socioeconomic-health gradient with endogenous health status. Based on the working-age population, Capatina, Keane, and Maruyama (2018) differentiate physical health shocks into multi-dimensions (e.g. permanent vs transitional, predictable vs unpredictable) and examine the effects on employment choice and human capital formation. Papageorge (2016) and Jolivet and Postel-Vinay (2024) look at the two-way interaction between work and health, where the former model medical treatment decisions and the latter model in a job search model with frictions.

Close to our paper are Hosseini, Kopecky, and Zhao (2021); Capatina and Keane (2023); De Nardi, Pashchenko, and Porapakkarm (2025), which emphasize the importance of health dynamics and income inequality in shaping life-cycle outcomes. Our study differs in two key aspects. First, we focus on the early career and the role of health in shaping initial occupational choices and human capital accumulation. Second, we abstract from modeling health insurance explicitly, as our interest lies in the formative stages of labor market entry and health transitions. Moreover, these studies focus on the U.S. context, where health insurance access is fragmented. Our study focuses on Australia, where universal health coverage weakens the insurance margin. The closest paper is Cozzi, Mantovan, and Sauer (2024), which shows that mental health exerts a stronger influence than physical health on career and family choices. Their focus, however, is on female labor supply and marriage decisions, while our analysis centers on the broader labor market dynamics and health transitions of young men.

The remainder of the paper is structured as follows. Section 2 describes the data and descriptive analysis. Sections 3 and 4 present the model and the maximum likelihood estimator, and Section 5 shows the model estimates. Section 6 presents counterfactual exercises, and Section 7 concludes by discussing the next steps.

2 Data and Background

In this section, we introduce the dataset used in the analysis, the Household, Income, and Labour Dynamics in Australia (HILDA), and highlight three key empirical patterns. First, we show that both mental and physical health are highly persistent: the probability of remaining in poor health, conditional on being in poor health, increases substantially over the life-cycle, while the probability of remaining in good health declines slightly with age. Second, using event study analyses, we demonstrate that life-shock events lead to transitory but significant short-term declines in health. Lastly, we examine the two-way relationship between health and occupational choices, highlighting the persistent negative effects associated with not working.

2.1 HILDA

Household, Income and Labour Dynamics in Australia (HILDA) is a nationally representative annual household-based panel survey of around 17,000 Australians since 2001. We use rich data on labor market characteristics, demographics, health measures, and life shock events, which are measured annually. Life shock events, which are key to our analysis, are asked since 2002, hence, our sample starts from 2002 and covers around 20 years. We focus on men after high school graduation from age 18 or less than 3 years of working experience up to age 41. After the data cleaning process, we have 2,294 men and 16,725 individual-year observations. Appendix A describes in detail the construction of variables and the final dataset.

Figure 1 provides an overview of choices in our sample: schooling, working, and not working. At age 18, around 40% of individuals are attending college which decreases steadily until age 25. The majority of our sample is employed,[5] while the share of non-working individuals is initially high at younger ages but stabilizes at around 10% from the mid-20s through age 41.

[5] The working population includes both paid and self-employed workers.

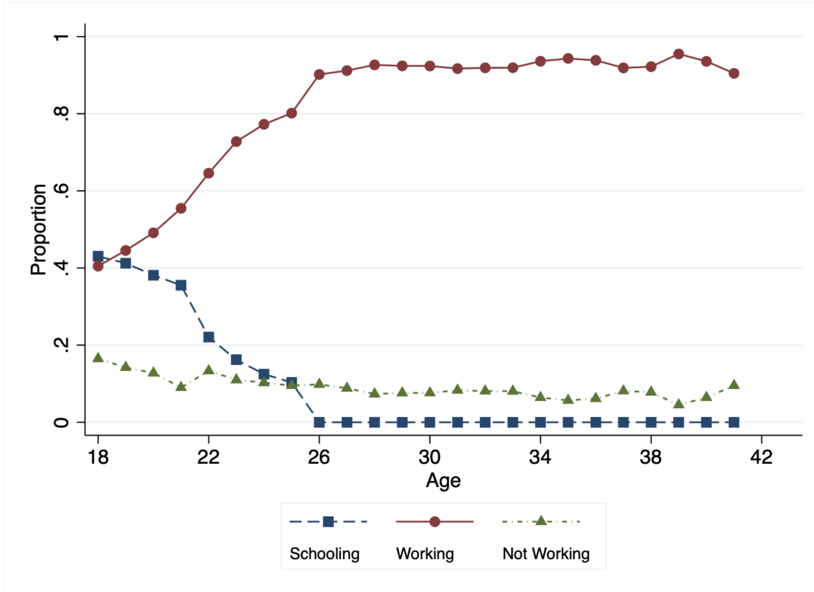


Figure 1: Occupation Choice by Age

For the health measures, we use scores derived from the 36-item Short-Form (SF-36) survey, which was first developed by Ware Jr and Sherbourne (1992) from the Medical Outcomes Survey and is widely used to evaluate health related quality. SF-36 can be categorized into eight 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 further divide into mental and physical health component.[6]

For mental health, we use the Mental Health Inventory (MHI-5) and is commonly used in the medical and psychology literature (Berwick et al., 1991; Rumpf, 2001; Cuijpers et al., 2009; Bech et al., 2001). Some papers using HILDA have used this measure to examine mental health and employment status (Crowe and Butterworth, 2016), social support (Milner et al., 2016), and job loss (Bubonya et al., 2017). MHI-5 is composed of five questions: How much of the time during the past 4 weeks, *1) Have you been a nervous person?, 2) Have you felt so down in the dumps that nothing could cheer you up?, 3) Have you felt calm and peaceful?, 4) Have you felt down?, and 5) Have you been a happy person?* For each question, respondents answer from a scale of 1 (All of the time) to 6 (None of the time). For consistency, we re-scale the score from 0 to 100 and reverse code if necessary such that a higher score implies better mental health. For the cutoff, we follow Kelly and al. (2008) and set the cutoff point to 60 out of 100 and create a binary mental health status: good (higher than 60) and poor (60 or lower).[7]

[6]It is recommended in the epidemiology and public health literature to not construct a single measure of health-related quality (Lins and Carvalho, 2016).

[7]We use a cutoff of 60 for the MHI-5. Thorsen et al. (2013) identify 52, 60, 68, and 86 as candidate thresholds, and explicitly apply 60 to distinguish individuals at risk of long-term sickness absence. Kelly and al. (2008) assess the performance of various MHI-5 cutpoints using ROC curve criteria and show that 60 minimizes misclassification when compared to the GHQ-12, balancing sensitivity and specificity. Other papers use different cutoffs, e.g. Hoeymans

For physical health, we use the SF-36 physical health component which consist of physical functioning, role physical, bodily pain, and general health. Instead of using a single measure, we take the average of the four scales. For the cutoff, we plot the density function and set it to that yields the same distribution - 80 or higher for good and poor, otherwise.[8] Since both health measures do not have official cutoffs, we support the validity of the health measures in Appendix C.

In Table A.4, we present summary statistics by occupation. In our sample, 79% of individuals report having good mental health and 78% having good physical health. Health outcomes vary systematically across occupations: those enrolled in college exhibit the highest rates of both good mental and physical health, followed by those who are employed. In contrast, individuals who are not working report the lowest levels of both mental and physical health. Examining by health status, we observe similar trends in that not working are more likely to experience poor mental and physical health. Among working individuals, the differences in health status are less pronounced; however, there is a clear disparity in annual income based on health status. Those with good mental health earn the highest on average, followed by those with good physical health.

To identify exogenous variation in health, we use life-shock events that are plausibly exogenous to individual health trajectories. The HILDA survey asks annually whether respondents experienced any significant life shock events in the last 12 months. These questions cover personal events such as marriage, pregnancy, loss of job, and death of spouse, as well as external events such as death of friend or relative, and worsening of financial situations. Among them, we use five specific questions: experiencing a death of friend, serious illness of relative, and death of relative, and being victim of property and physical violence. We use these events to show exogenous variation in our health measures, which directly affect both mental and physical health and indirectly affect individual schooling occupational choices and income. In Appendix D, we further prove the reasoning and validity of our instruments for mental and physical health.

2.2 Health Persistence

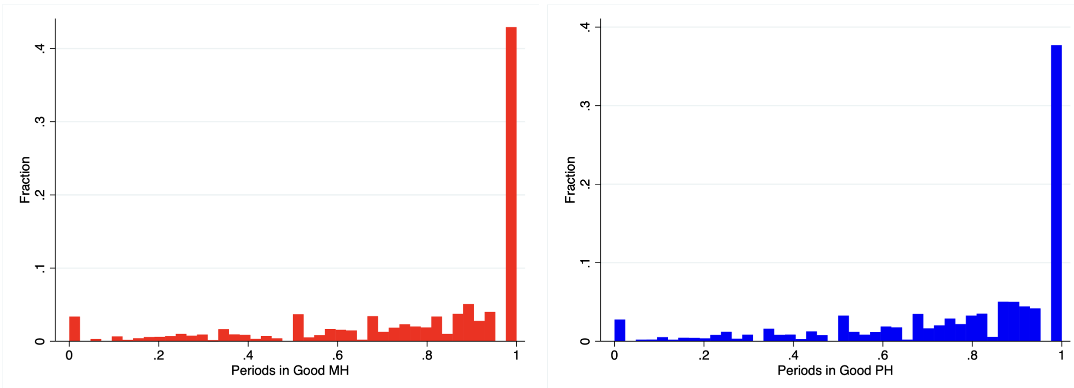
Figure 2 shows the distribution of the fraction of periods individuals spend in good mental and physical health. There is notable mass at 1, where 42.94% of individuals are always in good mental health, and 37.69% are always in good physical health; however, to better highlight variation across individuals, we show those who are not continuously in good health.

Conditional on not being always healthy, we observe substantial heterogeneity in both mental

et al. (2004) set as 72, Crowe and Butterworth (2016) set as 50, Bültmann et al. (2006), Holmes (1998) set as 52, Cuijpers et al. (2009) set 54 and 74. However, the cutoff by Kelly and al. (2008) seems most adequate for our study since the authors also use longitudinal data.

[8] Although there is no consensus for the physical health cutoff, we follow this method for both mental and physical health since our mental health cutoff is cross-validated by the medical and psychology literature. Similarly, Jolivet and Postel-Vinay (2024) use SF-12 (a shorter version of SF-36) and construct their health measures using the health score distribution and discretize into four states.

and physical health. The distributions are right-skewed, indicating that many individuals spend the majority of periods in good health. However, there is a non-negligible mass at the lower end—particularly in mental health—where some individuals are never in good health. We also see a spread in the middle consisting of individuals who are in good health roughly half of the time.



(a) Good Mental Health

(b) Good Physical Health

Figure 2: Fraction of Periods in Good Health

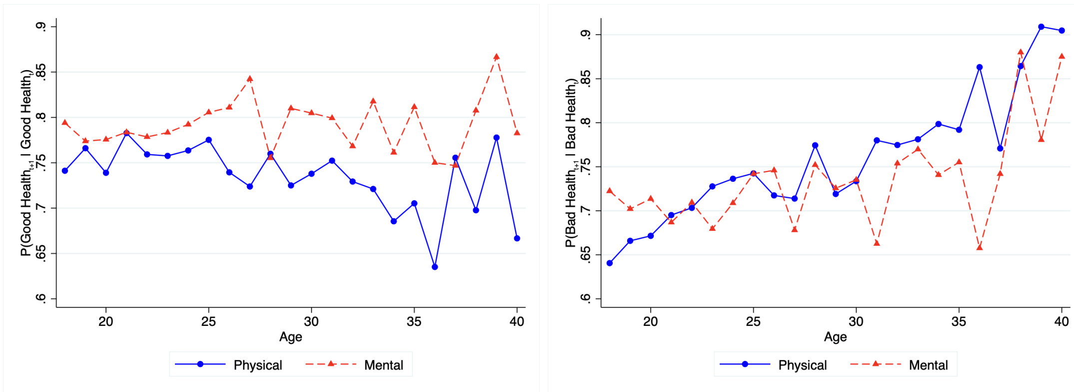
Note: For each individual in the sample, we compute the proportion of periods spent in good mental and physical health and plot the distributions. 42.94% of individuals are always in good mental health and 37.69% are always in good physical health.

To understand the health dynamics over age, we analyze the probabilities of maintaining or transitioning between states of good and bad mental and physical health in subsequent periods, conditional on current health status. The left panel of Figure 3 shows the probability of maintaining good health given current good health. The average probability is around 80% for mental health and 75% for physical health, indicating a marginally higher persistence in good mental health compared to physical health. The right panel shows the probability of experiencing bad health next period conditional on current bad health. The likelihood increases by age and is more pronounced for physical health. Unlike the probability of maintaining good health, there is a steeper and more consistent decline in physical health relative to mental health as individuals age.

Overall, we illustrate that both mental and physical health move in the same direction, even in similar magnitudes, suggesting that health status is both interdependent and persistent. Individuals who are currently in good health are more likely to remain so in the near future, while those in poor health are more likely to continue experiencing poor health.

2.3 Short-Term Impacts of Exogenous Life-Shock Events

Leveraging life shock events as instruments, we conduct event-study analyses to examine the short-run impacts of negative life events on health and labor market outcomes. We follow the



(a) Good Health

(b) Poor Health

Figure 3: Health Persistence

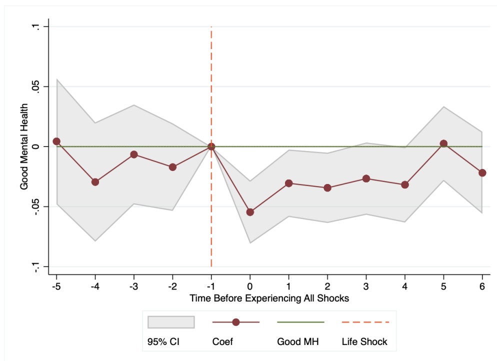
specification proposed by Sun and Abraham (2021), estimating the following regression:[9]

$$y_{gt} = \alpha + \sum_{k=T_0}^{-5} \beta_k \cdot z_{gk} + \sum_{k=0}^{6} \beta_k \cdot z_{gk} + X_t\Gamma + \gamma_t + \epsilon_{gt} \tag{1}$$

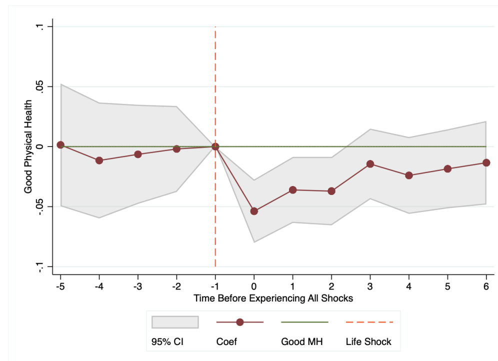
where y_{gt} denotes the outcome variables - good mental health, good physical health, and unemployment status - for individual g in year t, and z_{gk} is a set of event-time indicators capturing years relative to the life shock. The controls X_t include age and education, and γ_t denotes year fixed effects. Standard errors are clustered at the individual level. This setup allows us to trace the dynamic response of health around the timing of the life shock and isolate the immediate and persistent effects on both health dimensions.

Figure 4 shows that life shock events have a clear and immediate negative impact on both mental and physical health, especially in the short run. We observe a sharp decline in the probability of being in good health right after experiencing a life shock event, followed by a gradual recovery over the next one to three years. The decline is steeper and more persistent for mental health, which shows a slower return towards baseline health. It is interesting to note that health does not fully return to pre-shock levels. These patterns highlight the short-term disruption caused by life shocks. However, because the event-study framework focuses only on the first occurrence of a shock, it may underestimate the potential longer-term effects on health outcomes. We also observe a rise in unemployment following life shocks, although the effect fades quickly. This suggests short-term disruptions in labor market attachment, which may have potential longer-run implications for individuals with poor health. We provide additional robustness checks and

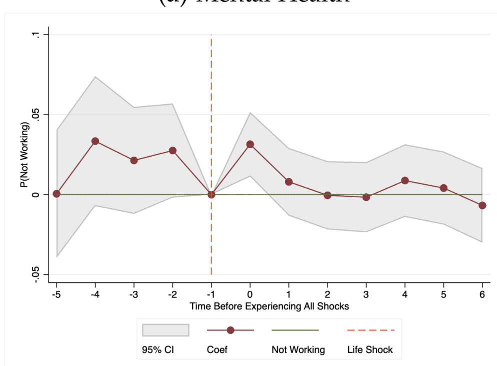
[9]In our dataset, some individuals never experienced any life shock events, whereas some experienced several times in different data periods; therefore, we follow the specification of Sun and Abraham (2021) to allow staggered treatments. For this exercise, we take the earliest year the individuals experienced the health shock, e.g. If one experienced a death of friend in 2008 at age 29, we take 2008 as the *treatment* year. Although the division between treatment and control group lacks granularity, we attempt to show that experiencing negative life events affect current health and health in the following periods.



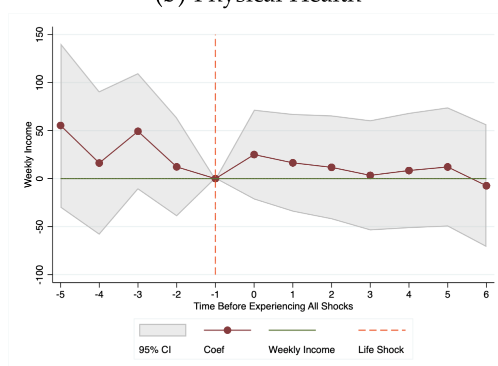
(a) Mental Health



(b) Physical Health



(c) Not Working



(d) Weekly Income

Figure 4: Event Study Analysis of Life Shocks

Note: The event includes whether or not the individual experienced at least one of the following life shocks: death of friend, victim of property crime, victim of physical violence, death of relative, serious illness of relative. The outcome corresponds to good mental and physical health.

validation exercises in Appendix D.

2.4 Two-Way Relationship Between Health and Occupation

In Table 1, we present the movement between occupations based on mental and physical health. In general, not working individuals with good mental or physical health are much more likely to enter employment in the subsequent period, of around 50% compared to 28–29% for those in poor health. Schooling is highly persistent regardless of health, but transitions from schooling to work are slightly more common among those in good health. Overall, the results suggest that both health dimensions are important factors of entering the labor force.

Table 1: Transition Matrix by Health Status

		Time $t+1$		
Poor MH		Schooling	Working	Not Working
Time t	Schooling	71.95	19.11	8.94
	Working	0.00	91.69	8.31
	Not Working	0.00	27.93	72.07
Good MH		Schooling	Working	Not Working
Time t	Schooling	77.13	19.20	3.68
	Working	0.00	96.97	3.03
	Not Working	0.00	51.54	48.46
Poor PH		Schooling	Working	Not Working
Time t	Schooling	68.49	22.60	8.90
	Working	0.00	92.93	7.07
	Not Working	0.00	28.01	71.99
Good PH		Schooling	Working	Not Working
Time t	Schooling	77.18	18.62	4.20
	Working	0.00	96.61	3.39
	Not Working	0.00	50.20	49.80

Note: Matrix input i, j represents the proportion of people in each occupation sector in row i who transitioned into occupation sector j from t to $t+1$ conditioning on health status.

For delve into the two-way interaction, we first examine the effect of occupation choice on mental and physical health. Table 2 shows the probability of having good health controlling for current health, occupation, income, and other demographic characteristics such as age and education. The linear probability model results indicate a significant positive correlation between current and future good health, affirming the persistence of health trends illustrated in Figure 3. Compared to not working, active engagement in the labor market or attending school appears to enhance overall health, particularly notable in cases where school attendance coincides with good physical health. After controlling for the life shock events as instruments, health persistence is more pronounced. The results imply that these exogenous life shocks have a pronounced and adverse impact on health, thereby influencing occupational choices.

Table 2: The Effect of Education and Occupation Changes on Health

	Good MH_{t+1}	Good PH_{t+1}
	OLS	OLS
	(1)	(2)
Variables at time t		
Health		
Good MH	0.330***	
	(0.013)	
Good PH		0.334***
		(0.013)
Life Shocks	-0.0156**	-0.0288***
	(0.007)	(0.007)
Education	0.00440**	0.00847***
	(0.002)	(0.002)
Age	-0.00331	-0.00700
	(0.006)	(0.006)
$Age^2/100$	-0.00204	-0.000846
	(0.011)	(0.012)
Occupation (ref: Not Working)		
Schooling	0.0799***	0.0981***
	(0.015)	(0.015)
Working	0.0605***	0.0723***
	(0.015)	(0.015)
Annual Income	0.554***	0.570***
	(0.135)	(0.136)
_cons	0.477***	0.500***
	(0.076)	(0.080)
Ind	2,165	2,165
Observations	14431	14431

Note: Life shock events include death of friend, victim of property crime, victim of physical violence, death of relative, and serious illness of relative. Standard errors are in parentheses. Annual income is measured in 1,000 AUD (deflated for 2015).

Next, we explore the effect of health on occupational choice and weekly income in Table 3. Controlling for health and current occupation, the likelihood of remaining in the same occupation is high, with a lower probability of transitioning to a different occupation. In terms of health, good health status significantly increases the likelihood of attending school and working. Looking at the effect of health in the intensive margin, both good mental and physical health are significantly associated with higher weekly income. Conditional on education and experience, individuals reporting good mental health earn approximately 714 AUD/week more, and those with good physical health earn about 540 AUD/week more.

Table 3: The Effect of Health on Education and Occupation Choice and Income

	Schooling$_{t+1}$ OLS (1)	Working$_{t+1}$ OLS (2)	Not Working$_{t+1}$ OLS (3)	Weekly Income OLS (4)
Variables at time *t*				
Health				
Good MH	0.0174	0.0375***	0.00181	0.0714***
	(0.022)	(0.007)	(0.006)	(0.015)
Good PH	0.0431*	0.0232***	-0.00354	0.0540***
	(0.024)	(0.007)	(0.005)	(0.015)
Occupation (ref: Not Working)				
Schooling		-0.279***	-0.0250***	
		(0.018)	(0.008)	
Working		0.446***	0.0348***	
		(0.018)	(0.007)	
Education				0.0964***
				(0.003)
Experience		0.0118***		0.128***
		(0.002)		(0.004)
Experience^2/100		-0.0561***		-0.375***
		(0.012)		(0.028)
_cons	0.883***	0.422***	0.0365***	-0.631***
	(0.028)	(0.020)	(0.007)	(0.044)
Ind	751	2,165	2,165	1,941
Observations	2508	14431	14431	12307

Note: Standard errors are in parentheses. We include age dummies for Column (1).

3 Dynamic Discrete Choice Model With Unobserved Heterogeneity

To study the dynamic health effects, we develop a dynamic discrete choice model with occupational choice and unobserved heterogeneity. The general structure follows Keane and Wolpin (1997) and we include mental and physical health as endogenous states, which are affected by previous health, occupation, and life shock events, income, and other demographic characteristics. We allow for unobserved heterogeneity in both income and health, and importantly, we let these unobserved components be correlated. Having two latent types and allowing them to be correlated is key to capturing individuals with low income but different health statuses, and vice versa.

Agents are assumed risk-averse and make choices on consumption and occupation based on their mental and physical health, education, experience, and preferences associated with each alternative. They face several forms of uncertainty: from mental and physical health, life shock events, and income. The model period $t \in \{1, ..., T\}$ is annual, starting at age 18 to 49, and agents make choices by maximizing their discounted future flow utility. At age 49, we assume agents remain in the same occupation sector until retirement age 65.[10] We assume that choices are age-dependent by restricting schooling option up to age 25.[11]

3.1 Choices and Flow Utility

Choices. We model unobserved heterogeneity along two dimensions: income and health. Each individual belongs to a latent type denoted by $k = (k_Y, k_H)$, where $k_Y \in \{1, 2\}$ captures income heterogeneity and $k_H \in \{1, 2\}$ captures health heterogeneity. This structure yields four latent types: [low income, poor health], [low income, good health], [high income, poor health], and [high income, good health]. We allow income heterogeneity to affect income and health types to influence both initial mental and physical health as well as their transitions over time. We capture the health correlations through factor loadings $\rho_{h,init}$ for initial health and ρ_h for health dynamics across periods.

In each period t, individuals of latent type k face a set of mutually exclusive choices $m \in \mathcal{M}$ where m can take values between attending school ($m = 1$), working ($m = 2$), and not working ($m = 3$). We denote $d_t^m \in \{0, 1\}$ as the indicator variable which equals 1 when alternative m is chosen and 0 otherwise.

State Variables. At the beginning of the model period, at age $a_1 = 18$, agents have initial endowments consisting of years of schooling $g_1 = 12$, experience $x_1 \in \{0, 1\}$, mental health mh_1, and physical health ph_1.[12] We denote this as the initial endowments $\boldsymbol{e}_1 = [g_1, x_1, mh_1, ph_1]$. In the subsequent periods, agents are characterized by a vector of initial endowments, observed state variables, and random preference shocks. The observed state vector $\mathbf{s}_t^o$ consists of years of schooling g_t, experience x_t, mental health mh_t, and physical health ph_t such that $\mathbf{s}_t^o = [g_t, x_t, mh_t, ph_t]$. The random shocks come from uncertainty in preferences, ε_t^m, mental and physical health, $\nu_{h,t}, h \in \{mh, ph\}$, life shock events, η_t, and income shocks, ξ_t^m.

Utility. In each period, the agent chooses occupation ($d_t^m, m \in \{1, 2, 3\}$) and consumption (C_t^m) in

[10]The assumption is based on data availability; since we start with individuals at age 18 or with less than three years of labor market experience and we use HILDA from 2001 to 2021, the full labor market history we observe of an individual is until age 41 and we exploit all information for our estimation. The continuation value upon retirement is normalized to zero.

[11]This assumption captures the fact that only 0.4% of individuals choose to attend college or graduate school after the age of 25. For details and reasoning, see Appendix F.

[12]We define that the individual has one year of experience if we observe her working at the initial period. This aligns with the survey timing and our definition of employment status and income. See Appendix A.

order to maximize their discounted expected utility:

$$\mathbb{E}\Big[\sum_{t=1}^{T=65} \beta^{t-1}[U(C_t^m, d_t^m)] + \beta^T \mathbb{E}[V_{T+1}(s_{T+1})]\Big] \tag{2}$$

where the within-period utility function is given by:

$$\begin{aligned} U(C_t^m, d_t^m) = u_t^m + \sum_{m=1}^{2}\Big[\phi_1^m + \phi_{h1}^m \mathbb{1}[mh_t = 1] + \phi_{h2}^m \mathbb{1}[ph_t = 1]\Big] \cdot d_t^m + \sum_{m=1}^{3} \phi_2^m \mathbb{1}[d_{t-1}^m = d_t^m] \\ + \phi_3^3 \mathbb{1}[d_{t-1}^3 = d_t^3] \cdot \mathbb{1}[mh_t = 1] + \phi_3^3 \mathbb{1}[d_{t-1}^3 = d_t^3] \cdot \mathbb{1}[ph_t = 1] + \varepsilon_t^m \\ \text{where} \quad u_t^m = \begin{cases} \psi_1^1 age + \psi_2^1 \mathbb{1}[graduate] & \text{if} \quad m = 1 \\ -exp(-\mu C_t^m) & \text{if} \quad m = 2,3 \end{cases} \end{aligned} \tag{3}$$

where agents face alternative-specific preference shocks, $\boldsymbol{\varepsilon}_t \in \{\varepsilon_t^1, \varepsilon_t^2, \varepsilon_t^3\} \sim T1EV$, independent across alternatives, periods, and individuals.

The flow utility has four main components. First, we assume that agents are risk averse, where $\mu \in [0, \infty)$ denotes the constant absolute risk aversion. Utility from schooling is not modeled through consumption but instead depends on age and school attendance status.[13] Second, we estimate the occupation-specific costs relative to not working, captured by $\phi_1^m, m \in \{1, 2\}$. For instance, ϕ_1^1 includes costs such as college or graduate school tuition and ϕ_1^2 captures the fixed costs associated to working.

The third component includes the alternative-specific utility benefits of good mental and physical health, denoted by ϕ_{h1}^m and ϕ_{h2}^m, $m \in \{1, 2, 3\}$. In particular, we allow the utility derived from health to vary by occupation choice because individuals typically exhibit different health status across occupations. This approach allows us to capture the strong correlation between not working and poor health. Moreover, the value of leisure is embedded in the utility both through the fixed costs and health costs. For instance, agents who choose schooling face tuition but accumulate human capital through higher education, potentially leading to higher earnings potentials and better health outcomes. Similarly, agents who choose to work gain work experience and higher income, which can mitigate the negative impact of health costs. On the other hand, those who do not work do not pay the fixed costs but may face lower income and higher health costs, which increases the disutility associated with not working.

Lastly, we add switching costs parameters $\phi_2^m, m \in \{1, 2, 3\}$ that allows us to capture occupational persistence. Individuals receive a utility gain when they remain in the same occupation as in the previous period, which reflects both the value of continuity and the frictions associated with changing occupations. Since unemployment is generally associated with poorer health, we

[13] The HILDA survey includes information on government allowances, such as the Youth and Austudy allowances, which provide support to individuals engaged in full-time study, apprenticeships, or job-seeking activities. Following Todd and Zhang (2020), we abstract from these transfers in our modeling.

include health-associated utility terms ϕ_3^3 and ϕ_4^3 to reflect the idea that those in good mental and physical health are more likely to exit unemployment.

3.2 Budget Constraint and Income Process

We assume no borrowing and saving, so consumption is determined by the following budget constraint:[14]

$$C_t^m = Y_t^m \tag{4}$$

where Y_t^m represents annual income associated with each alternative. Annual income is computed by multiplying weekly income y_t^m with the inelastic labor supply $\bar{\omega}^m$:[15]

$$Y_t^m = \bar{\omega}^m \times y_t^m \quad \text{if } m \in \{2, 3\} \tag{5}$$

Weekly Income. Each period, individuals face income uncertainty from a stochastic component $\xi_t^2 \overset{iid}{\sim} N(0, \sigma_{\xi^2}^2)$. For workers, weekly income includes wages or salaries, net business income, and dividends. The income process follows a Mincerian specification (Mincer, 1958) and controls for mental and physical health to capture the direct health costs on earnings. We account for income dependencies by introducing the unobserved type through the constant $\omega_0^{k_Y}$:

$$y_t^m = \omega_{k_Y}^Y + \psi_1^m g_t + \psi_2^m x_t + \psi_3^m (x_t)^2/100 + \psi_{h1}^m \mathbb{1}[mh_t = 1] + \psi_{h2}^m \mathbb{1}[ph_t = 1] + \xi_t^m, k \in \{1, 2\} \tag{6}$$

For not working individuals, weekly income only depends on age. Since a fraction of them receive a positive amount, weekly income depends on the probability p_g^3 such that:[16]

$$y_t^4 = \begin{cases} \psi_0^3 + \psi_1^3 a_t + \psi_2^3 (a_t)^2/100 + \xi_t^3 & \text{with prob } p_g^3 \\ 0 & \text{with prob } 1 - p_g^3 \end{cases} \tag{7}$$

3.3 Law of Motion

Schooling and Experience. We specify the law of motion of education and occupation-specific experience which evolve in a deterministic way:

$$g_{t+1} = g_t + d_t^1 \tag{8}$$
$$x_{t+1} = x_t + d_t^2 \tag{9}$$

[14] The transfer made to the next period is captured through human capital accumulation including health.

[15] We follow this specification similar to Hamilton, Hincapié, and Salari (2024) because we do not model working hours and weekly income is the best measure for income per unit. For more details, see Appendix A.

[16] In our data, around 43% of not working individuals receive parent transfer or positive government allowances such as NewStart and Youth Allowances. For more details, see Appendix A

Years of schooling increases by one unit when agent decides to attend college ($12 < g_t \leq 16$) or graduate school ($g_t \geq 17$). Experience also increases by one unit when the agent works.

Life Shock Events. Based from our empirical findings, we use real life shock events as instruments to capture exogenous variation in health status. We capture the events through indicator variables, $z_t \in \{0, 1\}$, which takes value 1 if the individual experienced any of the five life shock events (e.g. death of friend, victim of physical violence, victim of property crime, death of relative, and serious illness of relative) and 0 otherwise. We assume that individuals face shocks $\eta_t \sim T1EV$ and the probability $p(z_t)$ is a function of age such that:

$$P(z_t) = \frac{exp(\delta_0 + \delta_1 a_t + \delta_2 (a_t)^2/100)}{1 + exp(\delta_0 + \delta_1 a_t + \delta_2 (a_t)^2/100)} \tag{10}$$

Mental and Physical Health For mental and physical health, we assume that true health $h_t, h \in \{mh, ph\}$ is observed. mh_t and ph_t are self-assessed mental and physical health scores between $[0, 100]$ derived from MHI-5 and SF-36 physical component and we discretize into good ($h_t = 1$) and bad ($h_t = 0$) following cutoffs $c_{mh} = 60$ and $c_{ph} = 80$ derived from data:[17]

$$\widetilde{h}_t = \mathbb{1}[h_t + \zeta_{h,t} \geq c_h] \tag{11}$$

The transitional probability of moving from health state i at period t to health state i' at period $t + 1$ is denoted by:

$$\pi^{i,i'}_{h,t+1}(d^m_t, \mathbf{s}_t | k_H) = p(h_{t+1} = i' | h_t = i, d^m_t, \mathbf{s}_t, k_H), \quad h \in \{mh, ph\} \tag{12}$$

where $\pi^{i0}_{h,t} + \pi^{i1}_{h,t} = 1, \forall i, \forall t, h \in \{mh, ph\}$. Health at period $t + 1$ is determined by current health, age, education, life shock events, occupation, income, and i.i.d shocks $\nu_{h,t} \sim T1EV$. Note that for initial mental and physical health, we specify a functional form and for the subsequent periods, we follow the transitional probabilities given by:

$$\begin{aligned}
\pi^{i,i'}_{h,t+1}(d^m_t, \boldsymbol{s}_t | k_H, z_t) &= \frac{exp\left[A_h\right]}{1 + exp\left[A_h\right]}, \\
\text{where} \quad A_h &= \rho_h \cdot \omega^H_{k_H} + \alpha_{h,1} h_t + \alpha_{h,2} z_t + \alpha_{h,3} g_t + \alpha_{h,4} a_t + \alpha_{h,5} (a_t)^2/100 + \sum_{m=1}^{2} \alpha^m_{h,6} \cdot d^m_t \\
&+ \alpha_{h,7} \sum_{m=2}^{3} Y^m_t \cdot d^m_t + \alpha_{h,8} a_t \cdot d^1_t, \quad k_H \in \{1, 2\}, h \in \{mh, ph\}
\end{aligned} \tag{13}$$

From the health transition probabilities, we aim to capture four main components. First is health persistence. Since our health measures are binary, we capture the likelihood of remaining in the

[17] In Section Appendix C and Appendix C, we describe in further detail on how we define the cutoffs and the levels of good and bad mental and physical health.

same mental and physical health state (all else equal) when α_{h1} is positive. Although health might be affected by life shocks, the persistence component allows us to control for individual resilience to these events. Second is the effect of the life shock events through α_{h2}. From our empirical analysis, we showed that these exogenous events are statistically significant and negatively associated on current mental and physical health, thereby affecting next period health.

The third component is the reverse causality between health and occupation, motivated from the two-fold relationship. Reduced-form estimates indicate that poor mental and physical health are linked to exiting the labor force the following period. Conversely, not working is associated with deteriorating health, even after accounting for current health, life shocks, and other external factors. Schooling and employment are positively correlated with good health, particularly mental health, and this relationship is further strengthened by the income generated from employment. Hence, we incorporate a mechanism where current occupation choice and income influence next period health, which subsequently affects occupation choice. Since we do not model schooling income, we add the interaction between age and schooling dummy to capture the "income effect" from schooling.

Lastly, we incorporate unobserved heterogeneity through the type constants $\omega^H_{k_H}$ and the factor loadings ρ_h. This allows the transitory effects of latent types to shape the evolution of health. We further distinguish between the permanent and transitory effects allowing the factor loadings for initial mental and physical health. The interaction between $\omega^H_{k_H}$ and the factor loadings introduces individual-specific persistence in both mental and physical health transitions, generating correlation across outcomes and over time that is not captured by observed characteristics. For identification, we normalize the factor loading for mental health to be 1.

3.4 Information Structure

Individual heterogeneity comes from i) unobserved latent types $k \in (k_Y, k_H)$, ii) ex ante endowments and iii) ex post shocks $[\boldsymbol{\varepsilon}_t, \boldsymbol{\nu}_t, \eta_t, \boldsymbol{\xi}_t]$. The preference shocks $\boldsymbol{\varepsilon}_t$, health shocks $\boldsymbol{\nu}_t$, and life event shocks η_t follow Type 1 Extreme Value distribution and income shocks $\boldsymbol{\xi}_t$ follow i.i.d. normal distribution.

For identification purposes, we set the timing as follows: At the beginning of each period t, individuals observe preference shocks ε^m_t, then choose alternative m that yields the maximum utility. If individuals choose not to work, they face the probability of receiving positive government allowance, p^3_g. Then, income shocks $\xi^m_t, m \in \{2, 3\}$ are realized. At the end of the current period, life shock events η_t and health shocks are realized $\nu_{h,t}, h \in \{mh, ph\}$, which determine the health transitions $\pi^{i,i'}_{h,t+1}(h_t, d^m_t, \mathbf{s}_t|k_H), h \in \{mh, ph\}$. Given this assumption, we assume that there is no uncertainty in the current utility when choices are made.

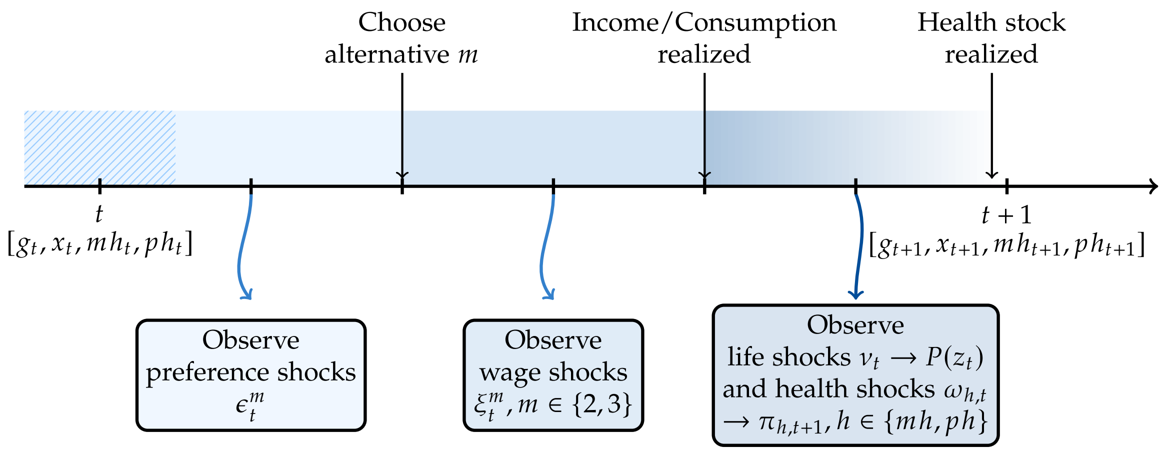


Figure 5: Model Timeline

3.5 Optimization Problem

In each period, agents maximize the expected present value of lifetime utility given current state conditional on unobserved type k, denoted by the value function:

$$V_t(\boldsymbol{s}_t|k) = \max_{d_t^m} \underbrace{\mathbb{E}_{\boldsymbol{\xi}_t}\mathbb{E}_{\eta_t}\mathbb{E}_{\nu_{h,t}} U(C_t^m, d_t^m, \boldsymbol{s}_t|k) + \delta\mathbb{E}_{\boldsymbol{\xi}_{t+1}}\mathbb{E}_{\eta_{t+1}}\mathbb{E}_{\nu_{h,t+1}}\mathbb{E}_{\boldsymbol{\varepsilon}_{t+1}} V_{t+1}(\boldsymbol{s}_{t+1}|k)}_{\Omega(C_t^m, d_t^m, \boldsymbol{s}_t|k)}$$
$$\text{s.t.} \quad C_t^m = Y_t^m \tag{14}$$

where $U(C_t^m, d_t^m, \boldsymbol{s}_t|k) = \widetilde{U}(C_t^m, d_t^m, \boldsymbol{s}_t|k) + \varepsilon_t^m$ and δ is the discount factor. More specifically, $\Omega(C_t^m, d_t^m, \boldsymbol{s}_t|k) = \mathbb{E}_{\boldsymbol{\xi}_t}\bar{\Omega}(C_t^m, d_t^m, \boldsymbol{s}_t|k)$, then we can write current utility and continuation value as:

$$\begin{aligned}
&\bar{\Omega}(C_t^m, d_t^m, \boldsymbol{s}_t) = U(C_t^m, d_t^m, \boldsymbol{s}_t) \\
&+ \delta \cdot p(z_t) \cdot \sum_{i'=0}^{1}\sum_{j'=0}^{1}\left[\pi_{mh,t+1}^{i,i'}(mh_t, \boldsymbol{s}_t|z_t = 1) \cdot \pi_{ph,t+1}^{j,j'}(ph_t, \boldsymbol{s}_t|z_t = 1) \cdot \mathbb{E}V_{t+1}(\boldsymbol{s}_{t+1})\right] \\
&+ \delta \cdot (1 - p(z_t)) \cdot \sum_{i'=0}^{1}\sum_{j'=0}^{1}\left[\pi_{mh,t+1}^{i,i'}(mh_t, \boldsymbol{s}_t|z_t = 0) \cdot \pi_{ph,t+1}^{j,j'}(ph_t, \boldsymbol{s}_t|k, z_t = 0) \cdot \mathbb{E}V_{t+1}(\boldsymbol{s}_{t+1})\right]
\end{aligned} \tag{15}$$

Given that the preference shocks follow a Type 1 Extreme Value distribution, we can derive the probabilities of choosing alternative m as:

$$p(d_t^m = 1|\boldsymbol{s}_t, k) = \frac{exp(\widetilde{\Omega}(C_t^m, d_t^m, \boldsymbol{s}_t|k))/\sigma_\varepsilon)}{\sum_{m=1}^{3} exp(\widetilde{\Omega}(C_t^m, d_t^m, \boldsymbol{s}_t|k)/\sigma_\varepsilon)} \tag{16}$$

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

$$\begin{aligned}\mathbb{E}[V_{t+1}(s_{t+1})|\boldsymbol{s}_t,k] &= \mathbb{E}_{\boldsymbol{\varepsilon}_t} \max_{d_t^m} \sum_{m=1}^{3}\Big[\widetilde{\Omega}(C_t^m,d_t^m,\boldsymbol{s}_t|k)+\varepsilon_t^m\Big] \\ &= \sigma_\varepsilon log\Big(\sum_{m=1}^{3} exp\Big(\frac{\widetilde{\Omega}(C_t^m,d_t^m,\boldsymbol{s}_t|k)}{\sigma_\varepsilon}\Big)\Big)+\sigma_\varepsilon\gamma\end{aligned} \tag{17}$$

where σ_ε is the standard deviation the preference shocks, common across all alternatives, and γ is the Euler constant.

For each type, we solve the model using backward induction beginning at the terminal period T. In the last period, agents do not have expected value function, hence, the value function is simply utility after integrating over the income shock distribution. This corresponds to the expected value function of the previous period, $\mathbb{E}[V(\mathbf{s}_T|k)|\mathbf{s}_{T-1},d_{T-1}^m]$, which allows us to identify the choices in the state space. Following the same process, we use $\mathbb{E}[V(\mathbf{s}_T|k)|\mathbf{s}_{T-1},d_{T-1}^m]$ for $\tilde{U}_t(C_t^m,d_t^m)$ to obtain $\mathbb{E}[V(\mathbf{s}_{T-1}^o|k)|\mathbf{s}_{T-2},d_{T-2}^m]$. We repeat until we reach the initial period and backward recursion allows us to obtain all the expected value functions at each possible state. We describe in more detail with the age specification in Appendix F.

4 Identification and Estimation

4.1 Identification

This section describes the identification strategy for the model parameters, leveraging variation in the data. The risk aversion parameter μ in the flow utility function is identified through observed variation in consumption patterns. For instance, periods of high income volatility lead individuals to varying levels of consumption risk, which allows us to estimate μ. Variation in occupational choices identifies the relative utility costs associated with schooling and working relative to not working, captured by the parameters $\phi_1^m, m \in \{1,2\}$. The health-related parameters, $\phi_{h1}^m, \phi_{h2}^m, m \in \{1,2,3\}$, are identified through differences in mental and physical health outcomes across occupational choices, with the health costs of not working normalized to zero, providing a reference point. Lastly, the switching costs, $\phi_2^m, m \in \{1,2,3\}$ are identified from observed persistence or switching of occupations, holding other determinants of utility constant. Condition on not working, we can also identify ϕ_3^3, ϕ_4^3 through variations in good mental and physical health status.

For the income equation parameters, individuals experiencing poor mental and physical health provide additional variation that identifies the health-related parameters for workers, specifically $[\psi_{h1}^2, \psi_{h2}^2]$. Furthermore, variation in individual characteristics such as age, education, and experience, as well as observed occupational choices, contributes to the identification of the remaining income parameters.

Parameters governing life shocks are identified through variation in the data, and these probabilities are treated as exogenous. The health transition probabilities are identified through variation in age, life shocks, occupation, income, and health status. The dynamic structure of the model ensures that the current health status is identified based on these variables and their interactions over time.

Unobserved heterogeneity is captured through type-specific constants: two income types $k_Y \in \{1,2\}$ and two health types $k_H \in \{1,2\}$. The resulting correlations across outcomes are governed by factor loadings: $\rho_{h,\text{init}}$ for initial mental and physical health (with $h \in \{mh, ph\}$), and ρ_h for health dynamics over time. For identification, we normalize the factor loading on mental health transitions to one. Identification relies on the finite mixture structure of the model, which recovers the type probabilities based on observed variation in health and labor market behavior. We allow income and health types to be correlated through the joint type probabilities $p^k = p(k_Y, k_H)$. This correlation structure is identified as long as health affects income differently across types and income variation cannot be fully accounted for by observables alone.

4.2 Maximum Likelihood Estimation

Since we observe the initial endowments of all agents in the data, we can express the estimation in a maximum likelihood function. The maximum likelihood estimator involves maximizing the joint probability of the observed occurrences. Agent $n \in \{1, ..., N\}$ of type k at each period $t \in \{t_1, ..., T\}$ chooses alternative m conditional on her current state and type. The MLE consists of various probabilities: i) type probability, p^k, ii) probability of observing initial mental and physical health, iii) probability of observing choices, $p(d_t^m = 1|\mathbf{s}_t, k)$, iv) probability of observing income $\widetilde{f}(y_t^m|k_Y)$, v) health transition probabilities $\pi_{h,t+1}^{i,i'}(h_t, \mathbf{s}_t|k_H), h \in \{mh, ph\}$, vi) probability of life shock events $P(z_t)$, and vii) probability of observing choice and income in the last period.

Denote the vector Θ to include all model parameters. The likelihood function of individual n

conditional on type k is written as:

$$
\begin{aligned}
&\mathcal{L}_n(\Theta|k) = \prod_{i=0}^{1} p(mh_{t_1} = i|k)^{\mathbb{1}[mh_{n,t_1}=i]} \cdot \prod_{j=0}^{1} p(ph_{t_1} = j|k)^{\mathbb{1}[ph_{n,t_1}=j]} \\
&\cdot \prod_{\tau=1}^{T_n-1} \prod_{m=1}^{3} \Bigg[P(d_\tau^m = 1|\boldsymbol{s}_t, k) \cdot \widetilde{f}(y_\tau^m|k_Y) \\
&\cdot \Bigg[P(z_\tau)^{\mathbb{1}[z_{n,\tau}=1]} \cdot \Bigg[\prod_{l'=0}^{1} \pi_{mh,\tau+1}^{l,l'}(mh_\tau, \boldsymbol{s}_t|k, z_t = 1)^{\mathbb{1}[mh_{n,\tau+1}=l']} \cdot \prod_{q'=0}^{1} \pi_{ph,\tau+1}^{q,q'}(ph_\tau, \boldsymbol{s}_t|k, z_t = 1)^{\mathbb{1}[ph_{n,\tau+1}=q']} \Bigg] \\
&\cdot (1 - P(z_\tau))^{\mathbb{1}[z_{n,\tau}=0]} \cdot \Bigg[\prod_{l'=0}^{1} \pi_{mh,\tau+1}^{l,l'}(mh_\tau, \boldsymbol{s}_t|k, z_t = 0)^{\mathbb{1}[mh_{n,\tau+1}=l']} \cdot \prod_{q'=0}^{1} \pi_{ph,\tau+1}^{q,q'}(ph_\tau, \boldsymbol{s}_t|k, z_t = 0)^{\mathbb{1}[ph_{n,\tau+1}=q']} \Bigg] \Bigg] \Bigg]^{\mathbb{1}[d_{n,\tau}^m = 1|\mathbf{s}_t, k]} \\
&\cdot \prod_{m=1}^{3} \Bigg[P(d_{T_n}^m = 1|\boldsymbol{s}_{T_n-1}, k) \cdot \widetilde{f}(y_{T_n}^m|k_Y) \Bigg]^{\mathbb{1}[d_{n,T_n}^m = 1|k]}
\end{aligned} \tag{18}
$$

where the probability of observing income is defined as:

$$
\widetilde{f}(y_t^m|k_Y) = \begin{cases} \left[p_g^3 \cdot \phi\left(\dfrac{y_t^3 - \hat{y}_t^3}{\sigma_{\xi^3}} \right) \right]^{\mathbb{1}[y_t^3 > 0]} \cdot \left[1 - p_g^3 \right]^{\mathbb{1}[y_t^3 \leq 0]} & \text{if } m = 3 \\ \tilde{\phi}\left(\dfrac{y_t^2 - \hat{y}_t^2}{\sigma_{\xi^2}} \right) & \text{if } m = 2 \end{cases} \tag{19}
$$

where $\hat{y}_t^m$ is the mean of the deterministic component of the wage equation and $\phi(\cdot)$ is the pdf of a standard normal distribution.

The first line shows the probability of being in observed in good or bad mental and physical health in the initial period (a_1). Lines 2 to 4 show the observed choices in the subsequent periods up to period T_n. We multiply the probability of choosing each alternative m given state $\mathbf{s}_t$ by the life shock probabilities and health transition probabilities. Lastly, line 5 shows the the probability of the last observed choice, which is similar to the initial condition setting.

For each individual likelihood, we sum over the types:

$$
\mathcal{L}_n(\Theta) = \sum_{k=1}^{4} p^k \mathcal{L}_n(\Theta|k) \tag{20}
$$

where $p^k \in [0, 1]$ is the probability of observing type k with the functional form:

$$
p^k = \frac{\exp\left(\lambda_0^k + \lambda_1^k fe_1 + \lambda_2^k \mathbb{1}[fe_1 = \text{missing}] + \lambda_3^k me_1 + \lambda_4^k \mathbb{1}[me_1 = \text{missing}] + \lambda_5^k iw_1\right)}{\sum_{\ell=1}^{4} \exp\left(\lambda_0^\ell + \lambda_1^\ell fe_1 + \lambda_2^\ell \mathbb{1}[fe_1 = \text{missing}] + \lambda_3^\ell me_1 + \lambda_4^\ell \mathbb{1}[me_1 = \text{missing}] + \lambda_5^\ell iw_1\right)} \tag{21}
$$

We model type probabilities as a function of early-life family background, including parental education and initial family wealth. We use indicators for whether the father (fe_1) and mother (me_1) completed high school, based on survey responses collected when individuals were 14 years old. These variables proxy initial conditions, given robust evidence linking higher parental education to better child health outcomes.[18] To address missing parental education data, we include missing indicators in the model to maximize the sample. In addition, we incorporate initial wealth (iw_1) to capture the influence of family resources on long-term health. Since initial wealth is heavily right-skewed, we use its inverse hyperbolic sine transformation.[19] This specification allows latent types to reflect systematic differences in family background, enabling us to capture selection into income-health types.

Finally, the likelihood for the entire sample is:

$$\mathcal{L}(\Theta) = \prod_{n=1}^{N} \mathcal{L}_n(\Theta) \tag{22}$$

Initial Conditions. To determine the probability of mental and physical health in the first period, we set the initial conditions based on health type and age. We can write the initial health transitional probabilities as:

$$\begin{gathered} P(h_{t_1} = 1 | k_H) = \frac{exp\left[\Lambda^h\right]}{1 + exp\left[\Lambda^h\right]},\ h \in \{mh, ph\} \\ \text{where } \Lambda^h = \rho_{h,init}\omega^H_{k_H} + \omega_{h,1}\mathbb{1}[a_1 > 18], \quad k_H \in \{1, 2\}, h \in \{mh, ph\} \end{gathered} \tag{23}$$

Given the lasting impact of initial health on behavior and outcomes, it is essential to account for persistent unobserved differences across individuals. We incorporate unobserved heterogeneity by including health-type-specific constants and allow initial mental and physical health to be correlated through factor loadings $\rho_{h,init}$, for $h \in \{mh, ph\}$. These parameters capture the joint structure of initial health, allowing us to model the early-life dynamics of mental and physical health more flexibly.[20] This structure enables us to separate persistent health traits from transitory fluctuations, with the latter captured by the health transition equations.

5 Parameter Estimates and Health Dynamics

This section describes the model results and use the estimates to evaluate the model fit and simulate occupation choices and health dynamics over time. We provide more details on the

[18] See, for example, Kestilä et al. (2006); Lindeboom, Llena-Nozal, and van Der Klaauw (2009); Chou et al. (2010); Ross and Mirowsky (2011); Aslam and Kingdon (2012).

[19] For details on variable construction, see Appendix Appendix A.

[20] As shown in Appendix Appendix C, mental and physical health are strongly correlated at baseline, with a correlation of approximately 0.45.

model algorithm in Appendix F.

The estimation proceeds in two stages. In the first stage, we jointly estimate the type probabilities, factor loadings, income process, initial health, and health transitions. This step enables us to account for unobserved heterogeneity and estimate the income processes, initial mental and physical health, and type probabilities. Additionally, we estimate, outside the model, the income processes for not working individuals and the probability of life shocks. In the second stage, conditional on the parameters estimated in the first stage, we estimate the utility parameters using the structural model.

5.1 First Stage Estimates

5.1.1 Joint Estimation

To jointly estimate the type probability, factor loadings, income processes, initial health, and health transitions, we estimate the following likelihood. This is feasible because the other components entering the individual type-specific likelihood are not type-dependent, and thus can be integrated out over types. As a result, we can focus on the type-dependent parts while treating the rest as common across types, simplifying the computation of the likelihood.

$$\mathcal{L}_n(\Theta|k) = \prod_{i=0}^{1} P(mh_{t_1} = i|k_H)^{\mathbb{1}[mh_{n,t_1}=i]} \cdot \prod_{j=0}^{1} p(ph_{t_1} = j|k_H)^{\mathbb{1}[ph_{n,t_1}=j]}$$
$$\cdot \prod_{\tau=1}^{T_n-1} \left[\widetilde{f}(y_\tau^m|k_Y) \cdot \prod_{l'=0}^{1} \pi_{mh,\tau+1}^{l,l'}(mh_\tau, \boldsymbol{s}_t|k_H)^{\mathbb{1}[mh_{n,\tau+1}=l']} \cdot \prod_{q'=0}^{1} \pi_{ph,\tau+1}^{q,q'}(ph_\tau, \boldsymbol{s}_t|k_H)^{\mathbb{1}[ph_{n,\tau+1}=q']} \right] \cdot \widetilde{f}(y_{T_n}^m|k_Y) \tag{24}$$

Initial Health. Table 4 presents the type constants, probabilities, and the initial health parameters. For interpretation, we can label income type 1 as ”low income” and income type 2 as ”high income.” Similarly, health type 1 corresponds to ”poor health” and health type 2 to ”good health.”

The probabilities of latent group types vary systematically with family characteristics. Higher parental education is associated with a lower likelihood of being in the poor health type. Similarly, greater family wealth is positively correlated with better health and increases the likelihood of belonging to the high income type. The factor loadings $\rho_{h,init}$, $h \in \{mh, ph\}$ capture the correlation between the latent factor and initial health conditions. The loading for mental health is larger than that for physical health, indicating that the latent factor is more strongly associated with variation in initial mental health than in physical health. This also reflects the structure of unobserved heterogeneity in health such that mental health discrepancies are more pronounced and better explained by the latent type. Since health plays a key role in human capital accumu-

Table 4: First-stage Parameter Estimates: Type and Initial Health

	Types			
	Estimate	SE		Estimate
$k_Y = 1$	-0.569	0.039	$p(k_Y = 1, k_H = 1)$	0.315
$k_Y = 2$	0.389	0.043	$p(k_Y = 1, k_H = 2)$	0.504
$k_H = 1$	0.208	0.077	$p(k_Y = 2, k_H = 1)$	0.062
$k_H = 2$	2.289	0.113	$p(k_Y = 2, k_H = 2)$	0.119

	$p(k_Y = 1, k_H = 1)$		$p(k_Y = 1, k_H = 2)$		$p(k_Y = 2, k_H = 1)$	
	Estimate	SE	Estimate	SE	Estimate	SE
Constant	1.357	0.180	1.455	0.193	0.023	0.300
Father's educ	-0.347	0.184	-0.323	0.181	-0.589	0.299
Missing father's educ	0.349	0.315	-0.110	0.322	-0.697	0.586
Mother's educ	-0.181	0.200	0.095	0.197	-0.186	0.333
Missing mother's educ	0.296	0.386	0.342	0.387	0.869	0.594
Initial wealth	-0.074	0.063	0.072	0.062	-0.134	0.102

	Initial MH		*Initial PH*	
	Estimate	SE	Estimate	SE
Factor loading	1.270	0.087	1.042	0.075
Age > 18	-0.064	0.119	-0.046	0.111

Note: Initial health probabilities from equation 23. Standard errors are in parentheses. Initial wealth is measured in 10,000 AUD. We use the inverse hyperbolic sine for initial wealth.

lation and labor market participation in the model, individuals starting with low latent health, especially in mental health, may face disadvantages over time.

Health Transitions. The health transitions in Table 5 show clearer life-cycle health patterns. The positive coefficient for current health indicates that health is indeed persistent; individuals in good health are more likely to remain so in the next period. Life shock events negatively impact health, with a more pronounced effect on physical health. This negative coefficient mainly affects short-term physical health, but it also ripples through mental health, impacting both health dimensions. While health generally declines with age, mental health deteriorates less than physical health, which is reflected in the persistence in Figure 3. Relative to not working, school is negatively associated with good mental health tomorrow but not for physical health, which suggests that the effect of schooling differs across health domains. The coefficients on the occupation dummies capture the two-way interactions between health and occupation. Working both positively associated with good health, with a slightly higher effect of mental health.

Weekly income. Table 6 shows the income process for workers, where labor supply, education, experience, and health are consistently important factors at the intensive margin. Controlling for occupation-specific and cross-occupation experience, we find that higher human capital, proxied by years of education and experience, is associated with higher income with diminishing returns and better health also contributes to higher income. Since the parameters are estimated jointly within the structural model, we account for selection into occupations, mitigating concerns about

Table 5: First-stage parameter estimates: Health Transitions

	Mental Health		*Physical Health*	
	Estimate	SE	Estimate	SE
Factor loading	1	-	0.815	0.045
Current health	1.339	0.061	1.333	0.056
Life shocks	-0.172	0.057	-0.324	0.053
Years of education	0.018	0.015	0.056	0.013
Age	-0.078	0.017	-0.078	0.016
$\text{Age}^2/100$	0.075	0.035	0.040	0.032
Schooling dummy	-0.880	0.615	0.065	0.653
Working dummy	0.224	0.095	0.219	0.091
Annual income	0.004	0.001	0.003	0.001
Schooling × Age	0.057	0.030	0.016	0.032

Note: Income equations for working individuals in paid employment and self-employment from equation 13. Annual income is measured in 1,000 AUD.

selection bias.

Table 6: First-stage parameter estimates: Weekly income

	Working Income	
	Estimate	SE
Years of education	0.081	0.003
Experience	0.116	0.003
$\text{Experience}^2/100$	-0.335	0.021
Good mental health	0.054	0.013
Good physical health	0.049	0.013
Variance of income shock	0.501	0.007

Note: Income equations for working individuals in paid employment and self-employment from equation 6. Income is measured in weekly income in 1,000 AUD. Standard errors are in parentheses.

5.1.2 Other First Stage Parameters

Life shock probability and not working income. Life shocks occur exogenously as a function of age and are estimated separately from the model to avoid endogeneity concerns and ensure that their occurrence is not influenced by other model variables. - which we have shown from the empirical analysis that it is a good instrument.

Similarly, we model income for not working individuals as a function of age, where they receive government allowance with probability p_g^4. Table 7 reports the estimates.

Table 7: First-stage parameters: Life Shocks and Not Working Income

	Life Shocks		*NW Weekly Income*	
	Estimate	SE	Estimate	SE
Constant	-1.263	0.458	-0.404	0.080
Age	0.022	0.035	0.040	0.006
$Age^2/100$	-0.057	0.066	-0.060	0.012

Note: Life shock probability from equation 10 and not working income is from equation 7. We estimate the log of weekly income for not working individuals conditioning on them receiving positive government allowance with probability $p_g^3 = 0.439$. Standard errors are in parentheses.

5.2 Second Stage estimates

Utility. Using the first stage estimates, we estimate the utility parameters internally in the second stage. Table 8 presents the estimated coefficients. Risk aversion is important in our context because health is volatile and persistent, introducing uncertainty into both current utility and future outcomes. Risk aversion implies that the model agents are relatively more willing to accept this uncertainty when making occupational choices. In particular, it affects how they trade off short-term income against long-term health and utility consequences, especially when their income is limited and health shocks are difficult to insure against.

Table 8: Structural Parameters: Utility

	Utility	
	Estimate	SE
Risk aversion	0.131	0.0002
Schooling: age	-0.338	0.0005
Schooling: graduate dummy	2.902	0.002
Schooling dummy	2.915	0.011
Working dummy	1.522	0.003
Schooling: good mh	0.569	0.002
Schooling: good ph	0.616	0.002
Working: good mh	0.440	0.002
Working: good ph	0.323	0.002
If schooling last period	3.635	0.002
If working last period	0.772	0.002
If not working last period	2.354	0.004
Not working last period X good MH	-0.144	0.003
Not working last period X good PH	-0.260	0.003

Note: Structural model estimates of flow utility from equation 3. Consumption is measured in 1,000 AUD.

Compared to not working, agents gain non-pecuniary benefits from attending school and working. This is consistent with the human capital accumulation literature, where individuals forgo current income for future earnings potential. If they choose to go to graduate school, the utility benefits are even higher, since higher education contributes to higher earnings potentials. Since the agents are forward-looking, they weigh these costs against the expected returns.

Health plays a crucial role in shaping utility, with strong heterogeneity across dimensions and occupations. Across all occupations, good health raises utility, but the effect is consistently stronger for mental health than for physical health. A key aspect of our paper is that by jointly modeling both mental and physical health, we are able to disentangle their distinct roles. While both dimensions affect income and decisions over work and schooling, our estimates show that mental health has first-order importance in shaping life-cycle behavior. These findings underscore the need to explicitly model mental health in dynamic settings where individuals make forward-looking decisions facing health uncertainty.

Regarding switching costs, we capture occupational persistence through state-dependent utility terms associated with last-period occupation. Persistence is the highest for schooling, not working, then working. These values suggest that individuals derive additional utility from staying in their current occupation, reflecting monetary and non-monetary benefits, and is strongest for schooling.

5.3 Model Fit

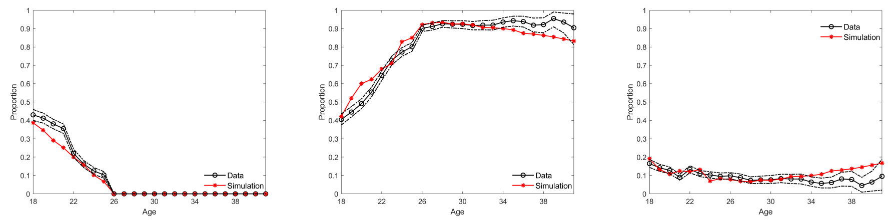
In general, our simulations align well with the observed data, capturing key life-cycle patterns across individuals. To evaluate the model's performance, we conduct four main exercises. First, we compare the occupational choices observed in the data with the predicted probabilities generated by the estimated model. This comparison allows us to assess the model's ability to replicate agents' decision-making processes. Figure 6 illustrates the results of this comparison. Note that an agent's occupational choice is influenced by a variety of factors, including life shocks that affect health, the dynamic relationship between current and future health, occupational choices, and the associated income. We capture well for schooling and working but slightly overestimate the not working rate after the late 30s. This discrepancy may reflect unmodeled heterogeneity in preferences that depend on health that is not fully captured in the model.

Nevertheless, the model's ability to replicate both occupational choices and health trajectories suggests that it effectively captures the bidirectional relationship between occupation and health. This reflects how occupational choices can impact health outcomes and, conversely, how health status can influence occupational opportunities and decisions. The two-way interactions are crucial for understanding the relationship between labor market dynamics and health over the life cycle, which is a key feature of our framework.

Second, we evaluate the model fit for income across occupations. Figure 7 shows that the model performs well in capturing income patterns for both working and not working individuals, although high for the early ages.

We also compare the life-cycle mental and physical health of the data and the model. Figure 8

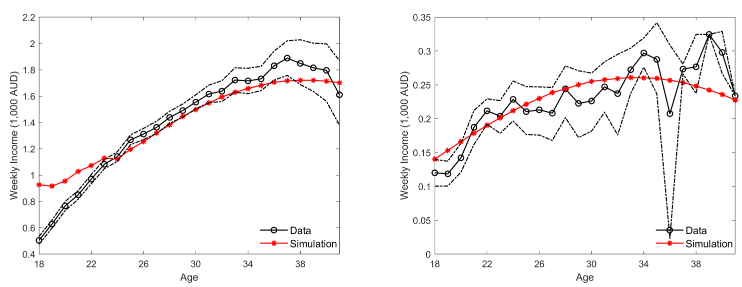
Figure 6: Data and Model Fit For Life-cycle Occupation Choices



(a) Schooling (b) Paid Employed (c) Not Working

Note: The dotted lines correspond to the 95% confidence interval around the data, calculated using 10,000 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.

Figure 7: Data and Model Fit For Weekly Income

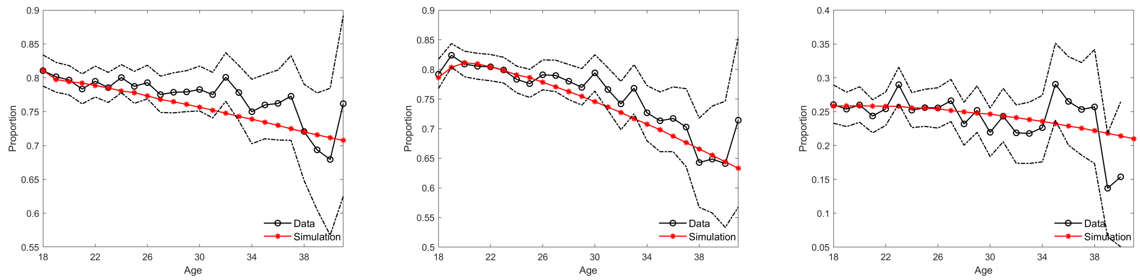


(a) Working (b) Not Working

Note: The dotted lines correspond to the 95% confidence interval around the data, calculated using 10,000 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.

shows that our model simulates well the declining mental and physical health over age.

Figure 8: Data and Model Fit for Life-cycle Mental and Physical Health and Life Shocks



(a) Mental Health (b) Physical Health (c) Life Shocks

Note: The dotted lines correspond to the 95% confidence interval around the data, calculated using 10,000 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.

Lastly, we compare the data and simulation for the transition matrices by health status, distinguishing between good and bad mental and physical health. Through the switching costs, we are able to replicate well the diagonals that capture the persistence in each occupation across periods. However, we overestimate the persistence in not working for individuals in good mental health as we may be overstating the utility of staying out of work for those with good health.

Table 9: Data and Model Transition Matrix by Health Status

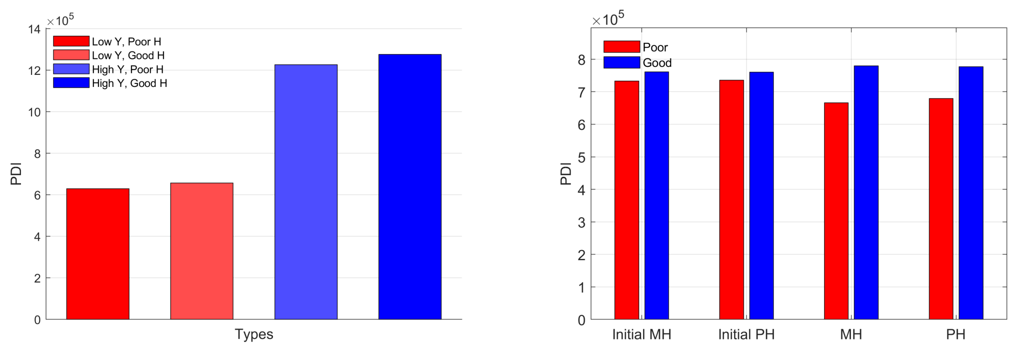
Health	Time t	Schooling	Working	Not Working
Poor MH				
	Schooling	71.95 / 75.87	19.11 / 21.28	8.94 / 2.85
	Working	0.00 / 0.09	91.69 / 94.09	8.31 / 5.83
	Not Working	0.00 / 0.60	27.93 / 37.09	72.07 / 62.35
Good MH				
	Schooling	77.13 / 76.02	19.20 / 21.80	3.68 / 2.19
	Working	0.00 / 0.12	96.97 / 94.97	3.03 / 4.91
	Not Working	0.00 / 0.91	51.54 / 43.41	48.46 / 55.69
Poor PH				
	Schooling	68.49 / 76.15	22.60 / 20.98	8.90 / 2.87
	Working	0.00 / 0.07	92.93 / 94.15	7.07 / 5.78
	Not Working	0.00 / 0.58	28.01 / 37.04	71.99 / 62.38
Good PH				
	Schooling	77.18 / 75.98	18.62 / 21.84	4.20 / 2.21
	Working	0.00 / 0.13	96.61 / 94.97	3.39 / 4.90
	Not Working	0.00 / 0.93	50.20 / 43.57	49.80 / 55.51

6 Counterfactual Analyses

Our model allows us to assess the direct impact of health, life shocks, and initial wealth on occupational choices and earnings. To do so, we simulate counterfactual life-cycle trajectories to examine the effect of poor health on occupation and income and the effect of unemployment and income shocks on health. Specifically, we fix the realizations of preference shocks, income shocks, types, and life-shock draws, and vary only the initial conditions of interest. This approach isolates the role of each factor in shaping schooling and occupation decisions, earnings, and discounted lifetime utility and income.

First, we compare the present discounted income (PDI) from ages 18 to 41, which we interpret as early to mid career discounted earnings, by unobserved latent types and health. The left panel of Figure 9 shows that those in the good health type earn more than those in the poor health type, and the difference is especially large when we compare across health and income types. In particular, individuals in the high income and good health type earn more than twice as much than those in the low income and poor health type.

In the right panel, the first two set of bars vary initial mental and physical health, while the last two sets of bars fix health status throughout the life-cycle. We see that initial health does not make a big long-term difference in PDI. However, when health is fixed, persistent good health leads to diverging income trajectories, especially for mental health. The gap is largest for mental health: those in poor mental health throughout earn much less than those in poor physical health, and those in good mental health earn more than those in good physical health. This underscores that mental health plays a more important role in shaping long-run earnings.



(a) By Unobserved Types

(b) By Health

Figure 9: Comparing Present Discounted Income

We illustrate this more clearly by comparing the percentage difference in present discounted income between those with poor and good health throughout the life cycle, conditional on income percentiles. Figure 10 shows that poor health increases inequality, and this effect is stronger for mental health. The gap in PDI between good and poor health is largest in the lower percentiles, highlighting the compounding disadvantage. Again, we are able to distinguish between the two health dimensions - the average PDI percentage difference is about 17.7% for mental health, compared to roughly 15.5% for physical health.

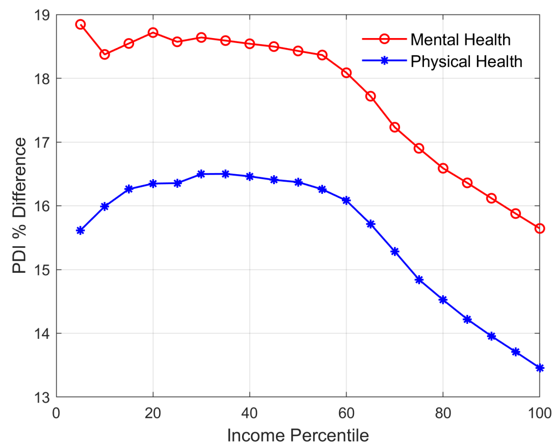
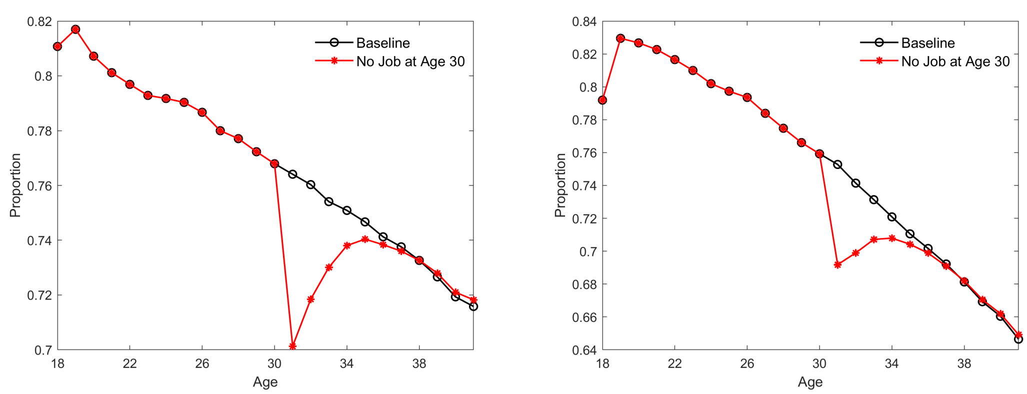


Figure 10: PDI % Difference by Health

Next, we look at the effect of unemployment on health. Both the empirical and structural results show that not working contributes to worse health outcomes, especially for mental health. We illustrate this through a counterfactual exercise where we put everyone into unemployment at age 30. Figure 11 shows that losing a job causes a stark decrease in mental health in the subsequent period, and it takes longer but at a faster rate to recover. This highlights how strongly unemployment affects mental health more than physical health.



(a) Mental Health (b) Physical Health

Figure 11: Counterfactual of Losing Job at Age 30

As robustness checks, we conduct additional counterfactual exercises, including the effects of poor health on income, and the impact of a two standard deviation decrease in income shocks on mental and physical health. We do not find strong effects on the intensive margin because most of the disparity comes from the extensive margin, from unemployment. However, when we compare present discounted income across scenarios, the differences become clearer as illustrated above. We also compare a range of outcomes, including present discounted income, present discounted utility, periods in each occupations and health under various conditions. We provide full details of these counterfactual exercises in Appendix E.

7 Conclusion

In this paper, we examine the role of both mental and physical health in shaping young men' schooling and occupational choices. Using rich longitudinal data, we document several empirical facts: mental and physical health are persistent, highly correlated, and sensitive to adverse life shocks, which in turn are linked to shifts in educational attainment and labor market participation.

Motivated by these patterns, we develop and estimate a dynamic structural model in which mental and physical health evolve endogenously and interact with individuals' occupational and schooling decisions. The model captures the two-way interactions between health and labor market outcomes, the persistence of health over the life-cycle, and the role of unobserved heterogeneity. We model unobserved heterogeneity by health and income types and allow them to be correlated in order to capture the transitory and permanent role of health into occupation and earnings.

Our counterfactual exercises reinforce these findings by showing how differences in latent types, initial health, and lifetime health shape long-run outcomes. We simulate various scenarios, including exogenous shocks to health and income, and examine their effects on present discounted income, utility, occupational paths, and periods in good health. We consistently find that individuals in better health and income types, with higher initial wealth and no major shocks, have higher lifetime earnings and utility.

We also find that mental health plays a larger role than physical health, widening inequality especially in lower income percentiles. Individuals in poor mental health are more vulnerable to income shocks and face larger losses in present discounted income. At the same time, good mental health can amplify these disparities, as those with better mental health accumulate higher earnings over time, further increasing the gap.

By jointly modeling mental and physical health dynamics and occupational choice, this paper provides a framework to study how health shapes individual decisions over the life-cycle. The model allows us to quantify the impact of early health conditions, life shocks, and family background on education, labor supply, and earnings. The paper highlights key margins where interventions, targeting mental health and early career conditions, can alter long-run trajectories. Our results underlines the importance of treating both mental and physical health as an integral part of human capital and a critical component of labor market outcomes.

References

Alexandre, Pierre K and Michael T French. 2001. "Labor supply of poor residents in metropolitan Miami, Florida: The role of depression and the co-morbid effects of substance use." Journal of Mental Health Policy and Economics 4 (4):161–174.

Aslam, Monazza and Geeta Gandhi Kingdon. 2012. "Parental education and child health—understanding the pathways of impact in Pakistan." World Development 40 (10):2014–2032.

Bech, P et al. 2001. "The sensitivity and specificity of the Major Depression Inventory, using the Present State Examination as the index of diagnostic validity." Journal of Affective Disorders 66 (2-3):159–164.

Berwick, Donald M et al. 1991. "Performance of a five-item mental health screening test." Medical Care :169–176.

Biasi, Barbara, Michael S Dahl, and Petra Moser. 2021. "Career effects of mental health." Tech. rep., National Bureau of Economic Research.

Bubonya, Melisa et al. 2017. "Job loss and the mental health of spouses and adolescent children." IZA Journal of Labor Economics 6 (1):1–27.

Bültmann, Ute et al. 2006. "Depressive symptoms and the risk of long-term sickness absence: a prospective study among 4747 employees in Denmark." Social Psychiatry and Psychiatric Epidemiology 41:875–880.

Capatina, Elena and Michael Keane. 2023. "Health shocks, health insurance, human capital, and the dynamics of earnings and health." Tech. rep., Federal Reserve Bank of Minneapolis.

Capatina, Elena, Michael P Keane, and Shiko Maruyama. 2018. "Health shocks and the evolution of earnings over the life-cycle." UNSW Business School Research Paper .

Chatterji, Pinka et al. 2007. "Psychiatric disorders and labor market outcomes: evidence from the National Latino and Asian American Study." Health Economics 16 (10):1069–1090.

Chou, Shin-Yi, Jin-Tan Liu, Michael Grossman, and Ted Joyce. 2010. "Parental education and child health: evidence from a natural experiment in Taiwan." American Economic Journal: Applied Economics 2 (1):33–61.

Churchill, Sefa Awaworyi and Russell Smyth. 2022. "Locus of control and the mental health effects of local area crime." Social Science & Medicine 301:114910.

Cornaglia, Francesca et al. 2014. "Crime and mental well-being." Journal of Human Resources 49 (1):110–140.

———. 2015. “Mental health and education decisions.” Labour Economics 33:1–12.

Cozzi, Guido, Noemi Mantovan, and Robert M Sauer. 2024. “How Important Are Mental and Physical Health in Career and Family Choices?” Tech. rep., IZA Discussion Papers.

Crowe, Laura and Peter Butterworth. 2016. “The role of financial hardship, mastery and social support in the association between employment status and depression: results from an Australian longitudinal cohort study.” BMJ Open 6 (5):e009834.

Cuijpers, Pim et al. 2009. “Screening for mood and anxiety disorders with the five-item, the three-item, and the two-item Mental Health Inventory.” Psychiatry Research 168 (3):250–255.

Currie, Janet and Mark Stabile. 2006. “Child mental health and human capital accumulation: the case of ADHD.” Journal of Health Economics 25 (6):1094–1118.

De Nardi, Mariacristina, Eric French, and John B Jones. 2010. “Why do the elderly save? The role of medical expenses.” Journal of Political Economy 118 (1):39–75.

De Nardi, Mariacristina, Svetlana Pashchenko, and Ponpoje Porapakkarm. 2025. “The lifetime costs of bad health.” Review of Economic Studies 92 (3):1987–2026.

Ettner, Susan L. 2000. “The relationship between labor market outcomes and physical and mental health.” Research in Human Capital and Development 13:1–31.

Ettner, Susan L et al. 1997. “The impact of psychiatric disorders on labor market outcomes.” ILR Review 51 (1):64–81.

Fadlon, Itzik and Torben Heien Nielsen. 2021. “Family labor supply responses to severe health shocks: Evidence from Danish administrative records.” American Economic Journal: Applied Economics 13 (3):1–30.

Fergusson, David M and Lianne J Woodward. 2002. “Mental health, educational, and social role outcomes of adolescents with depression.” Archives of General Psychiatry 59 (3):225–231.

Fletcher, Jason. 2013. “Adolescent depression and adult labor market outcomes.” Southern Economic Journal 80 (1):26–49.

Fletcher, Jason and Barbara Wolfe. 2008. “Child mental health and human capital accumulation: the case of ADHD revisited.” Journal of Health Economics 27 (3):794–800.

Fletcher, Jason M. 2008. “Adolescent depression: diagnosis, treatment, and educational attainment.” Health Economics 17 (11):1215–1235.

———. 2010. “Adolescent depression and educational attainment: results using sibling fixed effects.” Health Economics 19 (7):855–871.

Frank, Richard and Paul Gertler. 1991. "An assessment of measurement error bias for estimating the effect of mental distress on income." Journal of Human Resources 26 (1):154–164.

Freeman, Karen and Nadine Smith. 2014. "Understanding the relationship between crime victimisation and mental health: A longitudinal analysis of population data." NSW Bureau of Crime Statistics and Research .

French, Eric. 2005. "The effects of health, wealth, and wages on labour supply and retirement behaviour." The Review of Economic Studies 72 (2):395–427.

French, Eric and John Bailey Jones. 2011. "The effects of health insurance and self-insurance on retirement behavior." Econometrica 79 (3):693–732.

Friedland, Daniel S and Richard H Price. 2003. "Underemployment: Consequences for the health and well-being of workers." American Journal of Community Psychology 32:33–45.

Frijters, Paul et al. 2014. "The effect of mental health on employment: evidence from Australian panel data." Health Economics 23 (9):1058–1071.

Grossman, Michael. 1972. "On the concept of health capital and the demand for health." Journal of Political Economy 80 (2):223–255.

Haan, Peter and Michal Myck. 2009. "Dynamics of health and labor market risks." Journal of Health Economics 28 (6):1116–1125.

Hamilton, Barton H, Andrés Hincapié, and Mostafa Salari. 2024. "Entrepreneurial Dynamics and the Small-Firm Effect." Journal of Human Capital .

Hamilton, Vivian H et al. 1997. "Down and out: estimating the relationship between mental health and unemployment." Health Economics 6 (4):397–406.

Hiday, Virginia Aldigé, Marvin S Swartz, Jeffrey W Swanson, Randy Borum, and H Ryan Wagner. 1999. "Criminal victimization of persons with severe mental illness." Psychiatric Services 50 (1):62–68.

Hoeymans, Nancy et al. 2004. "Measuring mental health of the Dutch population: a comparison of the GHQ-12 and the MHI-5." Health and Quality of Life Outcomes 2:1–6.

Holmes, William C. 1998. "A short, psychiatric, case-finding measure for HIV seropositive outpatients: performance characteristics of the 5-item mental health subscale of the SF-20 in a male, seropositive sample." Medical Care :237–243.

Hosseini, Roozbeh, Karen A Kopecky, and Kai Zhao. 2021. "How important is health inequality for lifetime earnings inequality?" Tech. rep., Working paper.

Jacobs, Lindsay and Suphanit Piyapromdee. 2016. "Labor force transitions at older ages: Burnout, recovery, and reverse retirement." FEDS Working Paper :No. 2016–53.

Jolivet, Grégory and Fabien Postel-Vinay. 2024. “A structural analysis of mental health and labor market trajectories.” Review of Economic Studies :rdae071.

Keane, Michael P and Kenneth I Wolpin. 1997. “The career decisions of young men.” Journal of Political Economy 105 (3):473–522.

Kelly, Mark J and al. 2008. “Evaluating cutpoints for the MHI-5 and MCS using the GHQ-12: a comparison of five different methods.” BMC Psychiatry 8 (1):1–9.

Kessler, Ronald C and al. 2002. “Short screening scales to monitor population prevalences and trends in non-specific psychological distress.” Psychological Medicine 32 (6):959–976.

Kessler, Ronald C and Richard G Frank. 1997. “The impact of psychiatric disorders on work loss days.” Psychological Medicine 27 (4):861–873.

Kestilä, Laura, Seppo Koskinen, Tuija Martelin, Ossi Rahkonen, Tiina Pensola, Hillevi Aro, and Arpo Aromaa. 2006. “Determinants of health in early adulthood: what is the role of parental education, childhood adversities and own education?” European Journal of Public Health 16 (3):305–314.

Kouzis, Anthony C and William W Eaton. 1994. “Emotional disability days: prevalence and predictors.” American Journal of Public Health 84 (8):1304–1307.

Krekel, Christian and Marie Poprawe. 2014. “The effect of local crime on well-being: Evidence for Germany.” KOF Working Paper .

Lenhart, Otto. 2019. “The effects of health shocks on labor market outcomes: evidence from UK panel data.” European Journal of Health Economics 20 (1):83–98.

Lindeboom, Maarten, Ana Llena-Nozal, and Bas van Der Klaauw. 2009. “Parental education and child health: Evidence from a schooling reform.” Journal of Health Economics 28 (1):109–131.

Linn, Margaret W et al. 1985. “Effects of unemployment on mental and physical health.” American Journal of Public Health 75 (5):502–506.

Lins, Liliane and Fernando Martins Carvalho. 2016. “SF-36 total score as a single measure of health-related quality of life: Scoping review.” SAGE Open Medicine 4:2050312116671725.

Liu, Wai-Man, Liz Forbat, and Katrina Anderson. 2019. “Death of a close friend: Short and long-term impacts on physical, psychological and social well-being.” PloS one 14 (4):e0214838.

Lundborg, Petter, Anton Nilsson, and Dan-Olof Rooth. 2014. “Adolescent health and adult labor market outcomes.” Journal of Health Economics 37:25–40.

Mahler, Lukas and Minchul Yum. 2023. “Lifestyle behaviors and wealth-health gaps in Germany.” Available at SSRN 4034661 .

Mahuteau, Stéphane and Rong Zhu. 2016. "Crime victimisation and subjective well-being: Panel evidence from Australia." Health Economics 25 (11):1448–1463.

McKee-Ryan, Frances et al. 2005. "Psychological and physical well-being during unemployment: a meta-analytic study." Journal of Applied Psychology 90 (1):53.

Milner, Allison et al. 2016. "Age and gender differences in the influence of social support on mental health: a longitudinal fixed-effects analysis using 13 annual waves of the HILDA cohort." Public Health 140:172–178.

Mincer, Jacob. 1958. "Investment in human capital and personal income distribution." Journal of Political Economy 66 (4):281–302.

Ohrnberger, Julius et al. 2017. "The relationship between physical and mental health: A mediation analysis." Social Science & Medicine 195:42–49.

Ott, Carol H. 2003. "The impact of complicated grief on mental and physical health at various points in the bereavement process." Death Studies 27 (3):249–272.

Papageorge, Nicholas W. 2016. "Why medical innovation is valuable: Health, human capital, and the labor market." Quantitative Economics 7 (3):671–725.

Paul, Karsten I and Klaus Moser. 2009. "Unemployment impairs mental health: Meta-analyses." Journal of Vocational Behavior 74 (3):264–282.

Peng, Lizhong, Chad D Meyerhoefer, and Samuel H Zuvekas. 2013. "The effect of depression on labor market outcomes." Tech. rep., National Bureau of Economic Research.

Rodwell, Laura, Helena Romaniuk, Wendy Nilsen, John B Carlin, KJ Lee, and George Christopher Patton. 2018. "Adolescent mental health and behavioural predictors of being NEET: a prospective study of young adults not in employment, education, or training." Psychological Medicine 48 (5):861–871.

Ross, Catherine E and John Mirowsky. 2011. "The interaction of personal and parental education on health." Social Science & Medicine 72 (4):591–599.

Rumpf, Hans-Jürgen others. 2001. "Screening for mental health: validity of the MHI-5 using DSM-IV Axis I psychiatric disorders as gold standard." Psychiatry Research 105 (3):243–253.

Rust, John. 1987. "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher." Econometrica: Journal of the Econometric Society :999–1033.

Services Australia. 2024a. "Newstart Allowance." URL https://www.servicesaustralia.gov.au/newstart-allowance. Accessed: 2024-07-10.

———. 2024b. "Who can get Austudy." URL https://www.servicesaustralia.gov.au/who-can-get-austudy?context=22441. Accessed: 2024-07-10.

———. 2024c. "Youth Allowance." URL https://www.servicesaustralia.gov.au/youth-allowance. Accessed: 2024-07-10.

Stroebe, Margaret, Henk Schut, and Wolfgang Stroebe. 2007. "Health outcomes of bereavement." The Lancet 370 (9603):1960–1973.

Stroebe, Wolfgang and Margaret S Stroebe. 1987. Bereavement and Health: The Psychological and Physical Consequences of Partner Loss. Cambridge University Press.

Sun, Liyang and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." Journal of Econometrics 225 (2):175–199.

Teplin, Linda A et al. 2005. "Crime victimization in adults with severe mental illness: comparison with the National Crime Victimization Survey." Archives of General Psychiatry 62 (8):911–921.

Thorsen, Sannie Vester et al. 2013. "The predictive value of mental health for long-term sickness absence: the Major Depression Inventory (MDI) and the Mental Health Inventory (MHI-5) compared." BMC Medical Research Methodology 13 (1):1–7.

Todd, Petra E and Weilong Zhang. 2020. "A dynamic model of personality, schooling, and occupational choice." Quantitative Economics 11 (1):231–275.

Walsh, Froma and Monica McGoldrick. 2004. "Living beyond loss: Death in the family." WW Norton & Company .

Wang, Buyi, Richard Frank, and Sherry Glied. 2023. "Lasting scars: The impact of depression in early adulthood on subsequent labor market outcomes." Health Economics 32 (12):2694–2708.

Ware Jr, John E and Cathy Donald Sherbourne. 1992. "The MOS 36-item short-form health survey (SF-36): I. Conceptual framework and item selection." Medical Care :473–483.

Appendix A Variable and Data Construction

In this section, we describe in detail the important variables and walk through the final data cleaning process.

Years of Education: The Australian education system consists of primary, secondary, and tertiary education and school attendance is mandatory up to age 15 or 17, depending on the state.[21] The senior secondary school includes Year 11 and 12 and in the final year, students may study for a government-endorsed certificate in preparation for tertiary education. Following the Australian Qualifications Framework (AQF), there are Certificates I to IV and Diplomas for regulated qualifications. The AQF standardized into 10 different levels from Level 1 (Certificate I) to 10 (doctoral degree). Certificate I and II provide basic vocational skills and Certificate III and IV provide advanced skills, where the latter is equivalent to six to twelve months of degree study. Our sample is based on individuals who completed high school education with 12 years of schooling.

Schooling and Occupation Sector: The *schooling* category includes individuals who entered and/or currently enrolled in college or graduate school at time t after high school graduation. *Working* includes both paid and self-employed workers (worked mainly in their own businesses with or without employees) who, at time t worked in the past 7 days in any job, business or farm. Lastly, we define *not working* individuals as those who did not work for the past 7 days and were not paid in family business.

Working Weeks: We compute working weeks based on the percentage time spent in all jobs during the last financial year. This variable is used to compute the weekly income.

Not Working Weeks: Australia provides government support to individuals who are not working. First, Youth Allowance is for those aged 24 or younger, with age eligibility varying by activity such as full-time study, apprenticeship, or job seeking. Second, NewStart allowance is an unemployment benefit scheme for individuals with ages 22 to pension age 64, which was replaced by JobSeeker Payment on March 20, 2020. Hence, for 2021 data, we use JobSeeker as the income support payment.[22] For non-working individuals, we sum Youth and Newstart Allowances and then calculate the number of weeks they receive these government benefits.

Weekly income: We use weekly income as the income measure for working and not working individuals. First, for working individuals, we calculate the aggregate annual income, which is the sum of wage or salaries, profits from unincorporated business, profits from investments, and dividends from the last financial year. Then the sum is divided by the number of working weeks, defined as above. For not working individuals, we sum the Newstart and Youth Allowances received in the last financial year and then divide by the number of weeks received. If the respondents do not know their yearly amount, HILDA asks the average received per fortnight

[21] With minor variations across states and territories, school education is mandatory between ages 4/6-15/17 (Year 1 to 9 or 10).

[22] For more details, please refer to the descriptions provided by the Australian Government (Services Australia, 2024b,a,c).

and we divide it by two to compute their not working weekly income. Moreover, we include information on parent transfer, which is one of the important income sources for young adults. The weekly income is computed as follows:

- For working individuals ($m = 2$):

$$y_i^m = \frac{\text{wage/salary}_i + \text{net business income}_i + \text{dividends}_i}{\%\text{time spent} * 52/100}$$

- For not working individuals ($m = 3$):

$$y_i^m = \begin{cases} (\text{New Start} + \text{Youth Allowance})/\text{weeks received} + \text{parent transfer}/52 \\ \text{fortnight amount}/2 + \text{parent transfer}/52 \end{cases}$$

Annual Income: Annual income equals weekly income multiplied by inelastic labor supply. From Table A.1, we observe that around 44% of not working receive positive government allowances, with an average duration of 22 weeks. Workers on average work around 50 weeks per year. We use the average number of weeks as the inelastic labor supply $\bar{\omega}^m$.

Table A.1: Inelastic Labor Supply

	Obs	%	$\bar{\omega}^m$	Std. Dev
Working	12,281	.	49.19	8.84
Not Working	759	0.44	21.35	22.99

Initial Wealth: Information on household net worth is collected every four years starting from 2001 (wave 2, 6, 10, 14, and 18) and we use this information to control for individuals' initial conditions. We calculate initial wealth by subtracting the positive and negative values of household net worth and if necessary, use the imputed values from the HILDA survey. Since we only have quadrennial data, we use the household net worth at age $t' \leq t$ when the individual at age t. This covers 75.67% of individuals . For those missing, we use the next available wealth information (within the next four years) as initial wealth, which covers 88.85% individuals. For the remaining missing values, we impute running a regression on home ownership, imputed home value, age, age square, and education.

Experience: For individuals whom we observe since age 18, experience is set to zero. For those we do not observe the end of completed education or start of the career, we keep individuals who have less than 3 years of experience. We follow Hamilton, Hincapié, and Salari (2024) to create a the potential experience variable using two methods. We define the first measure as

$$\tilde{x}_0^1 \equiv age_0 - max\{\text{Years of education}, 16\} - 6$$

where the subindex 0 indicates that the measure is taken the first time we observe the individual at age greater than or equal to 22 and after leaving full-time education. Since this does not account for years not working and differences between years of certified education and actual number of years spent in school, we compute another measure. Let $a\bar{g}e_0$ be the maximum possible age of entry to the labor market defined as

$$a\bar{g}e_0 = age_0 - exp_0$$

where exp_0 indicates the labor market experience. Let the (approximate) labor market experience at age 22 be defined as:

$$exp_{22} = max\{0, 22 - a\bar{g}e_0\}$$

and τ^e be the number of years since the individual left full-time school. This is imputed by HILDA, in which constructed based on the sum of time in paid-work, time not working, and time looking for a job. Then the second measure is defined as

$$\tilde{x}_0^2 = \begin{cases} exp_0 - exp_{22} & \text{if} \quad exp_0 \quad \text{is observed} \\ \tau_0^e & \text{if} \quad exp_0 \quad \text{is missing} \end{cases}$$

Combining these two measures, we get potential experience defined as

$$\tilde{x_0} = \begin{cases} \tilde{x}_0^1 & \text{if only} \quad \tilde{x}_0^1 \quad \text{is observed} \\ \tilde{x}_0^2 & \text{if only} \quad \tilde{x}_0^2 \quad \text{is observed} \\ min\{\tilde{x}_0^1, \tilde{x}_0^2\} & \text{if both are observed} \end{cases}$$

Table A.2 shows the data cleaning process for the final dataset.

Table A.2: Our Sample Construction

	Individual-Year Observations	% kept	Individual	% kept
Initial Sample	433,115	100.00	45,570	100.00
Drop women and armed force	209,491	48.37	22,533	49.45
Drop if age< 18	154,344	35.64	17,460	38.31
Drop if missing education	147,274	34.00	15,534	34.09
Drop if less than high school graduation	111,864	25.83	11,695	25.66
Drop if missing labor market characteristics	96,112	22.19	9,895	21.71
Drop if missing health measures	84,273	19.46	9,519	20.89
Drop if missing life shock events	79,964	18.46	9,243	20.28
Keep if observe the start of career ($\tilde{x_0} \leq 3$)	17,996	4.16	2,706	5.94
Drop income outliers	17,765	4.10	2,700	5.92
Drop if missing consecutive years and age>41	16,781	3.87	2,294	5.03
Drop education outliers	16,725	3.86	2,294	5.03

Note: Since life shock events start from 2002, the final dataset includes years 2002 - 2021. We drop individuals who don't satisfy the condition: age ≥ education + paid employment experience + self employment experience + 5, where the age of entering primary school is around age 5-6.

Appendix A.1 Timing of the Variables

In this subsection, we describe the timing of the key variables from the survey interview because it is crucial for model timing assumption and understanding the information structure.

Table A.3 describes the timing of the variables. For instance, suppose an individual was interviewed in 2001. From this interview, we obtain information on their mental and physical health and employment status for 2001, as well as their life shock events and income for 2000. Similarly, in the 2002 interview, we gather information on their mental and physical health and employment status for 2002, along with life shock events and income for 2001.

To ensure consistency in measuring income, we assume that an individual remains in the same occupation for the entire financial year. Hence, we link income data collected in the 2002 interview to the occupation data from the 2001 interview. This approach ensures that income aligns with the reported occupation for the same financial year.

To instrument previous life shock events on current mental and physical health, and to examine their effects on future mental and physical health, we require three panel observations for each individual.

Variable	**Question**	**Timing**
Mental and physical health	*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? ... 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 any emotional problems (such as feeling depressed or anxious)?*	t
Life shocks	*We now would like you to think about major events that have happened in your life over the past 12 months.*	$t-1$
Employment status	*At any time at all during the last 7 days, did you do any work in a job, business or farm?*	t
Hours worked	*I am now going to ask you some questions about your main job. That is, the job in which you usually get the most pay from each week. Including any paid or unpaid overtime, how many hours per week do you usually work in your main job?*	t
% time spent	*Percent time spent in jobs last financial year.*	$t-1$
Income - wage/salary	*Last financial year, what was your total wage and salary income from all jobs before tax or anything else was deducted?*	$t-1$
Income - dividends	*Including only your share, what was your total income from dividends from your incorporated businesses in the last financial year?*	$t-1$
Income - business income	*Excluding dividends, in the last financial year, what was your total income from wages and salary from these incorporated businesses before income tax was deducted? Please exclude wages and salary already reported.*	$t-1$
Income - government allowances	*"I am now going to ask you about your receipt of government pensions, benefits and allowances during the last financial year. Looking at SHOWCARD F31, during the last financial year, did you receive any of these government pensions or allowances?"*	$t-1$
Income - parent transfer	*"How much did you receive from [specify source] during the last financial year?"*	$t-1$

Table A.3: Timing of Survey Questions

Appendix B Summary Statistics

Table A.4: Summary Statistics by Occupation and Health Status

	All	Schooling	Working	Not Working
Obs	16,725	2,690	12,307	1,728
Proportion	1	0.16	0.74	0.10
Good MH	0.79	0.82	0.81	0.61
Good PH	0.78	0.84	0.79	0.64
Age	25.18	20.52	26.36	23.98
	(5.27)	(1.97)	(5.20)	(4.97)
Years of education	13.32	14.28	13.18	12.87
	(2.16)	(1.81)	(2.22)	(1.80)
Annual income	50,836.93	-	56,356.72	25,080.66
	(40,449.92)	-	(39,097.46)	(32,464.18)

	All	Poor MH	Good MH	Poor PH	Good PH
Obs	16,725	3,567	13,158	3,612	13,113
Proportion	1	0.21	0.79	0.22	0.78
Schooling	0.16	0.14	0.17	0.12	0.17
Working	0.74	0.67	0.75	0.71	0.74
Not Working	0.11	0.19	0.08	0.17	0.08
Age	25.18	25.51	25.09	25.85	24.99
	(5.27)	(5.43)	(5.22)	(5.60)	(5.16)
Years of education	13.33	13.20	13.36	13.06	13.40
	(2.16)	(2.02)	(2.20)	(1.99)	(2.20)
Annual Income	50,836.93	43,035.34	53,022.14	45,324.86	52,460.90
	(40,449.92)	(39,411.89)	(40,468.94)	(40,925.30)	(40,166.69)
Initial Wealth	584,503.70	499,725.60	607,486.20	471,290.80	615,688.40
	(973,521.60)	(855,602.30)	(1,001,898.00)	(946,382.50)	(978,602.40)
Father's High School					
Yes	0.64	0.61	0.65	0.60	0.65
No	0.25	0.27	0.25	0.27	0.25
Missing	0.11	0.12	0.10	0.13	0.10
Mother's High School					
Yes	0.56	0.54	0.56	0.50	0.57
No	0.35	0.36	0.35	0.39	0.34
Missing	0.09	0.10	0.09	0.11	0.09

Note: Standard deviations are in parentheses. The observations are individual-year and the monetary units are in Australian dollars (deflated in 2015 AUD). Annual income includes wage/salaries, net business income, and dividends for working individuals and government allowances and parent transfers for not working individuals, conditional on receiving positive income.

Appendix C Validity of Health Measures

For mental and physical health, we use MHI-5 and SF-36 physical component and derive binary variables for good and bad health. Since the health measures do not have official cutoffs, we first plot the kernel density functions. Figure A.1 shows the density functions with the mean and median plotted vertically. We observe that both mental and physical health are left skewed and the score is generally higher for physical health. For our cutoffs, we use the median of 76 and 89 over 100 for mental and physical health, respectively.

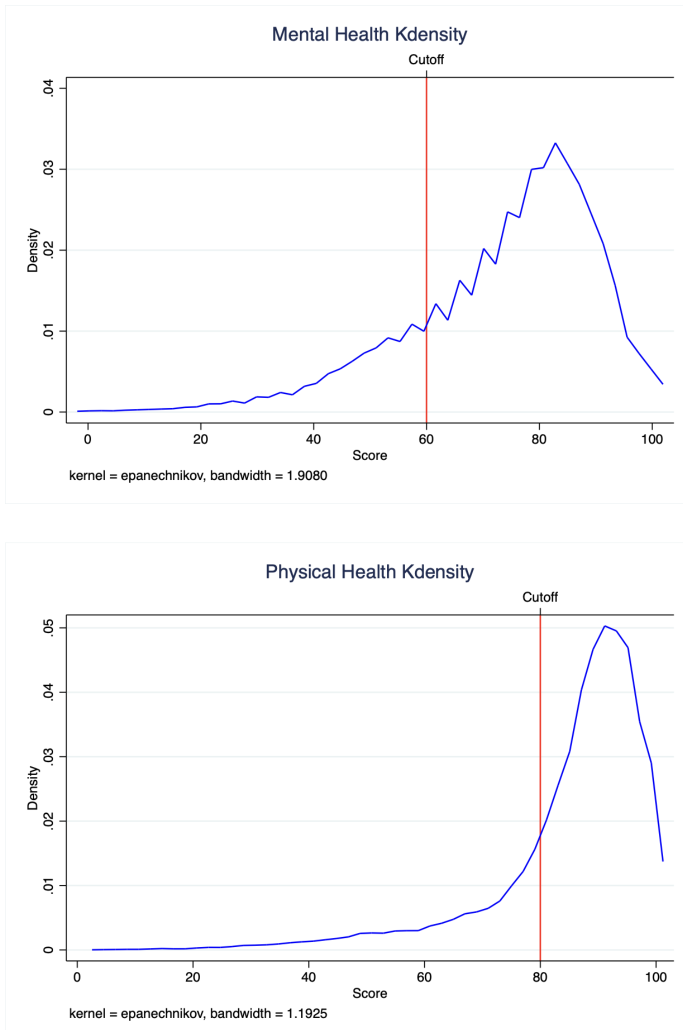


Figure A.1: Density Function of Health Measures

Note: In each figure, the solid vertical line shows the mean and the dotted vertical line shows the median.

To prove validity of our health measures, we compare with other health measures available in the HILDA survey. For mental health, HILDA also measures Kessler-10 (Kessler and al., 2002), which is a psychological screening tool to assess psychological distress. Kessler-10 consists of ten questions to measure anxiety and depressive symptoms during the last four weeks, e.g. *Did you feel full of life? Have you been a nervous person? Have you felt down?* For each question, respondents rank from 1 (All of the time) to 6 (None of the time) and the scores are re-scaled and reverse-coded such that a higher score implies better psychological health. Although Kessler-10 is a good indicator for mental health, we instead use MHI-5 because the latter is measured every year whereas Kessler-10 is measured biannually since 2007, which reduces our sample size.

For general health, we observe self-reported health and life satisfaction, where respondents scale from 0 (Totally dissatisfied) to 10 (Totally satisfied). Moreover, HILDA asks about general health status coded from 1 (Poor) to 5 (Excellent).

Table A.5 shows the correlation matrix of the different health measures. We observe that the correlation between mental and physical health is between 0.4 and 0.5 and is statistically significant at the 99% confidence level. For mental health, MHI-5 is highly correlated with the other measures SF-36 mental (0.85) and Kessler-10 (0.81). Similarly, SF-physical is highly correlated with general health satisfaction (0.52) and health status (0.54). In general, we show that the self-assessed mental and physical health measures are consistent with the other health measures we observe in the dataset.

Table A.5: Correlation Matrix of Health Variables

	MHI-5	SF-Physical
MHI-5	1	0.449***
SF-Mental	0.849***	0.563***
SF-Physical	0.449 ***	1
Kessler-10	0.806***	0.478***
Health satisfaction	0.420***	0.516***
Life satisfaction	0.499***	0.296***
Health Status	0.402***	0.537***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D Reasoning and Validity of Health Instruments

Among the life shock events asked in the HILDA survey, we use five questions to show exogenous variation in our health measures. The five instruments include experiencing a death of friend, serious illness of relative, or death of relative or being victim of property or physical violence.

We begin by explaining the reasoning behind the choice of instruments and their use in other studies. First, we consider the death of a close friend similar to Frijters et al. (2014), who demonstrate that such event has strong negative implications on health. The authors address the weak identification in a instrumental-variables fixed-effects setting and show that a death of a friend has short and long-term impacts on mental health, which, in turn affect employment outcomes.

Liu, Forbat, and Anderson (2019) also find that death of a close friend has negative and enduring consequences in both physical and psychological health.

Second, we include victimization from property crime and physical violence. Studies by Hiday et al. (1999), Teplin et al. (2005), and Mahuteau and Zhu (2016) indicate that crime victimization is closely related to mental well-being and have negative consequences. Moreover, Freeman and Smith (2014) and Cornaglia et al. (2014), using HILDA data, find that being a victim of violent crime results in adverse mental health effects for both men and women, although the effect was insignificant for property crime. However, Churchill and Smyth (2022) and Krekel and Poprawe (2014) provide evidence that local area crime affects mental health, supporting similar findings in the context of Germany.

In addition, we include death and serious injury or illness of relative into our analysis. Research underscores that a loss of close family members is strongly correlated with deterioration in both mental and physical health (Ott, 2003; Walsh and McGoldrick, 2004; Stroebe, Schut, and Stroebe, 2007). Bereavement not only has immediate and enduring implications but also influences individual labor supply decisions (Stroebe and Stroebe, 1987; Fadlon and Nielsen, 2021). Since death or serious illness of first-degree family such as spouse is more likely to directly impact occupational choices, we focus instead on relatives, which is more likely to affect individual health rather than directly influencing career decisions.

Table A.6: Summary Statistics of Life Shock Events

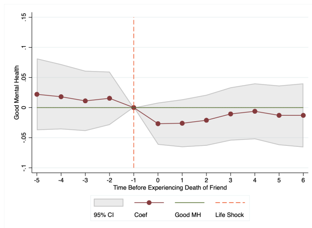
	Obs	Mean	Std. Dev
All	16,725	0.257	0.437
Death of Friend	16,725	0.058	0.233
Victim of Property Crime	16,725	0.049	0.216
Victim of Physical Violence	16,725	0.020	0.139
Serious Illness of Relative	16,725	0.097	0.295
Death of Relative	16,725	0.100	0.301

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

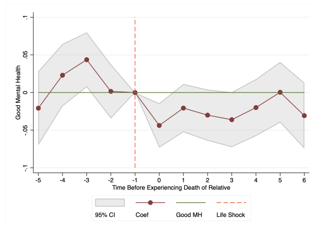
In our data, we observe that an average of 25% of individuals experience at least one of these life events each year (Table A.6). Specifically, 6% of respondents experienced a death of a friend 10% experienced the death or serious illness of a relative.

In addition to the main event study analyses, we provide plots for each life shock event on mental and physical health in Figures A.2 and A.3.

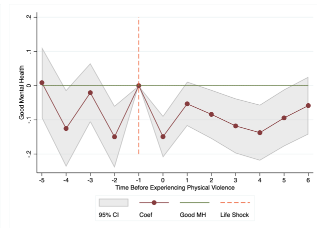
Figure A.2: Life Shock Events on Good Mental Health



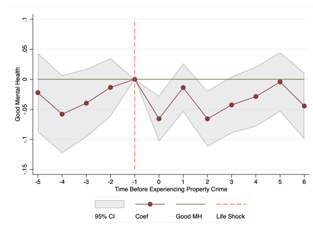
(a) Death of Friend



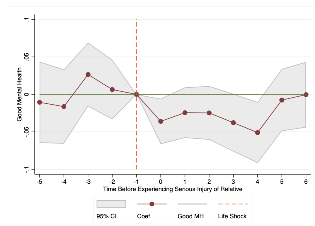
(b) Death of Relative



(c) Physical Violence

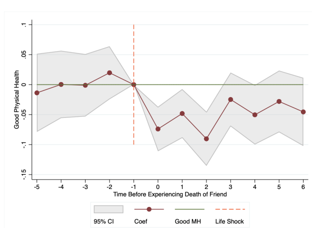


(d) Property Crime

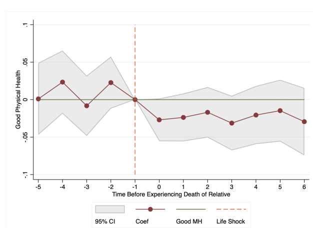


(e) Injury of Relative

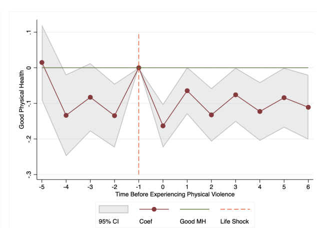
Figure A.3: Life Shock Events on Good Physical Health



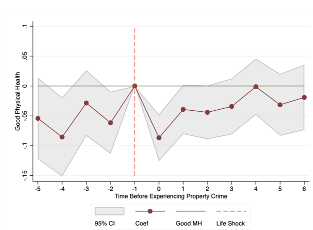
(a) Death of Friend



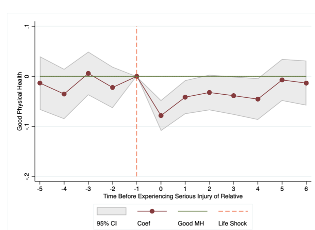
(b) Death of Relative



(c) Physical Violence



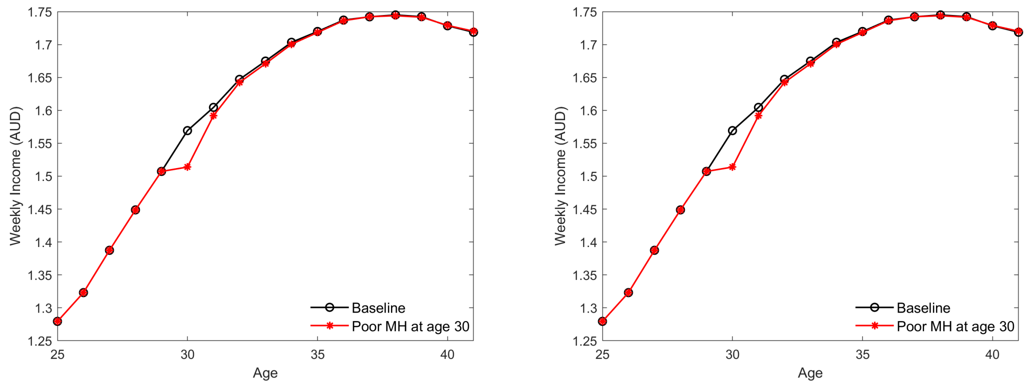
(d) Property Crime



(e) Injury of Relative

Appendix E Additional Counterfactual Results

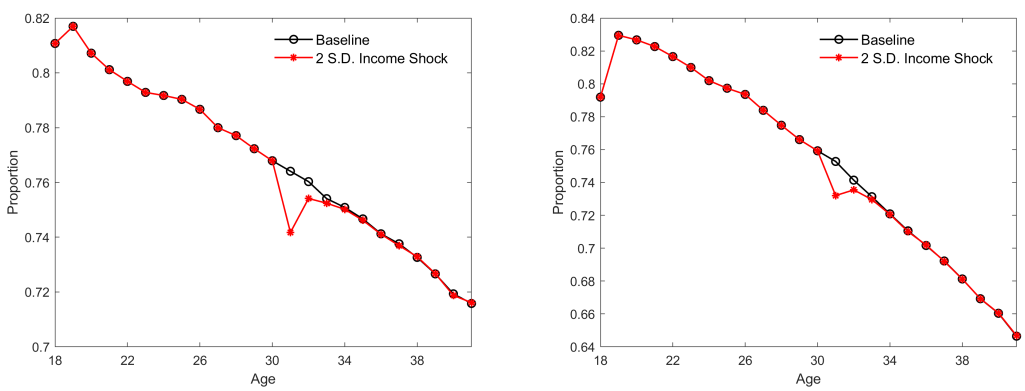
In this section, we provide additional exercises for our counterfactual analysis. We continue by looking at the effect of health on income and vice versa. Figure A.4 shows that there is a negative effect of poor mental or physical health at age 30 on income.



(a) Poor MH at Age 30 → Working Income (b) Poor PH at Age 30 → Working Income

Figure A.4: Poor Health on Income

Looking at it the other way around, we simulate the effect of two standard deviation decrease in income shocks on health. We see a clear drop in health, especially in mental health, with a longer recovery period compared to physical health.



(a) Working: Mental Health (b) Paid Working: Physical Health

For robustness, we compare various outcomes of interest including the present discounted income, present discounted utility, and periods in each occupation as well as in good mental and physical health. We compare them by unobserved latent types (Table A.7), initial mental and physical health (Table A.8), lifetime mental and physical health (Table A.9), life shock events (Table A.10), and initial wealth (Table A.11).

Overall, we find that individuals in better health and income types, with higher initial wealth and no major life shock events at different ages, tend to have higher discounted lifetime income and utility. These differences are primarily explained by earlier entry and longer duration in the labor force. Good health is strongly associated with more stable occupational paths, less years in unemployment, and higher overall well-being over the life cycle.

Table A.7: Simulated Outcomes by Types

	Types				
	Avg Wgt	(Low Y, Poor H)	(Low Y, Good H)	(High Y, Poor H)	(High Y, Good H)
PDI	757719.75	629300.99	657738.52	1227347.13	1276421.84
PDU	25.79	23.43	24.60	32.53	33.56
Years in SCH	4.25	4.79	4.91	1.41	1.48
Years Working	19.4	19.08	19.25	20.07	20.54
Years Not Working	3.57	3.77	3.32	4.34	3.66
Periods in Good MH	18.28	11.90	22.03	12.69	22.17
Periods in Good PH	17.93	12.49	21.26	12.42	21.17

Note: Using the estimated parameters, we simulate forward the life-cycle paths of individuals 100 times, starting at age 18. Throughout the counterfactual simulations, we hold fixed the realizations of preference shocks, income shocks, types, and life shock draws. From the data, we take other state variables - paid employment experience, self employment experience, years of schooling, initial mental health, and initial physical health - as given. We also classify data individuals into those in the bottom and top quartile of the initial wealth distribution. Then, we compare cases by types. For each individual, we compute discounted lifetime income, defined as the present value of paid employment income, self employment income, and/or not working income (government allowances), using a discount factor of $\delta = 0.95$. Discounted lifetime utility is calculated as the present value of flow utilities derived from the model solution.

Table A.8: Simulated Outcomes by Initial Mental and Physical Health

	Initial Mental Health		**Initial Physical Health**	
	Poor	Good	Poor	Good
PDI	732542.43	760823.87	735726.37	760422.79
PDU	19.67	27.15	20.84	27.04
Years in SCH	4.72	4.80	4.71	4.81
Years Working	18.90	19.51	19.02	19.49
Years Not Working	3.91	3.48	3.90	3.48
Periods in Good MH	17.38	18.69	18.40	18.45
Periods in Good PH	18.06	18.09	17.05	18.36

Note: Using the estimated parameters, we simulate forward the life-cycle paths of individuals 100 times, starting at age 18. Throughout the counterfactual simulations, we hold fixed the realizations of preference shocks, income shocks, types, and life shock draws. From the data, we take other state variables - paid employment experience, self employment experience, years of schooling, and initial mental or physical health - as given. In the top panel, we compare cases where initial mental health is set to either bad ($mh_1 = 0$) or good ($mh_1 = 1$), simulating their outcomes until age 41. Similarly, in the bottom panel, we compare cases where initial physical health is set to bad ($ph_1 = 0$) or good ($ph_1 = 1$). For each individual, we compute discounted lifetime income, defined as the present value of paid employment income, self employment income, and/or not working income (government allowances), using a discount factor of $\delta = 0.95$. Discounted lifetime utility is calculated as the present value of flow utilities derived from the model solution.

Table A.9: Simulated Outcomes by Mental and Physical Health

	Mental Health		**Physical Health**	
	Poor	Good	Poor	Good
PDI	666022.91	779314.82	679524.03	777192.57
PDU	16.72	27.95	18.16	27.85
Years in SCH	4.74	4.79	4.59	4.83
Years Working	17.77	19.82	18.12	19.76
Years Not Working	4.98	3.17	4.86	3.17
Periods in Good MH	1.00	23.86	18.30	18.50
Periods in Good PH	17.95	18.14	1.00	23.87

Note: *Note*: Using the estimated parameters, we simulate forward the life-cycle paths of individuals 100 times, starting at age 18. Throughout the counterfactual simulations, we hold fixed the realizations of preference shocks, income shocks, types, and life shock draws. From the data, we take other state variables - paid employment experience, self employment experience, and years of schooling - as given. In the top panel, we compare cases where mental health is set to either always bad ($mh_1 = 0$) or good ($mh_1 = 1$) throughout the life-cycle, simulating their outcomes until age 41. Similarly, in the bottom panel, we compare cases where initial physical health is set to always bad ($ph_1 = 0$) or good ($ph_1 = 1$) throughout the life cycle. For each individual, we compute discounted lifetime income, defined as the present value of paid employment income, self employment income, and/or not working income (government allowances), using a discount factor of $\delta = 0.95$. Discounted lifetime utility is calculated as the present value of flow utilities derived from the model solution.

Table A.10: Simulated Outcomes by Life Shock Events

	Life Shock at Age 25		**Life Shock at Age 35**	
	Yes	No	Yes	No
PDI	756971.80	756684.82	756971.80	756696.72
PDU	25.85	25.83	25.85	25.84
Years in SCH	4.79	4.79	4.79	4.79
Years Working	19.43	19.42	19.43	19.42
Years Not Working	3.54	3.55	3.54	3.55
Periods in Good MH	18.60	18.57	18.60	18.57
Periods in Good PH	18.42	18.36	18.42	18.35

Note: Using the estimated parameters, we simulate forward the life-cycle paths of individuals 100 times, starting at age 18. Throughout the counterfactual simulations, we hold fixed the realizations of preference shocks, income shocks, types, and life shock draws. From the data, we take other state variables - paid employment experience, self employment experience, years of schooling, initial mental and physical health - as given. In the top panel, we compare cases where individuals do not experience life shocks at age 25 ($z_{age=25} = 0$) or experience ($z_{age=25} = 1$), simulating their outcomes until age 41. Similarly, for the second counterfactual, individuals experience life shocks at age 35 or not.

Table A.11: Simulated Outcomes by Initial Wealth

	Initial Wealth	
	Bottom Q4	Top Q4
PDI	1009959.88	1030054.93
PDU	28.34	30.44
Years in SCH	4.35	4.31
Years Working	19.90	19.98
Years Not Working	3.70	3.64
Periods in Good MH	20.27	20.52
Periods in Good PH	19.59	19.81

Note: Using the estimated parameters, we simulate forward the life-cycle paths of individuals 100 times, starting at age 18. Throughout the counterfactual simulations, we hold fixed the realizations of preference shocks, income shocks, types, and life shock draws. From the data, we take other state variables - paid employment experience, self employment experience, years of schooling, initial mental health, and initial physical health - as given. We also classify data individuals into those in the bottom and top quartile of the initial wealth distribution. Then, we compare cases where individuals' initial wealth is the bottom or top quartile. For each individual, we compute discounted lifetime income, defined as the present value of paid employment income, self employment income, and/or not working income (government allowances), using a discount factor of $\delta = 0.95$. Discounted lifetime utility is calculated as the present value of flow utilities derived from the model solution.

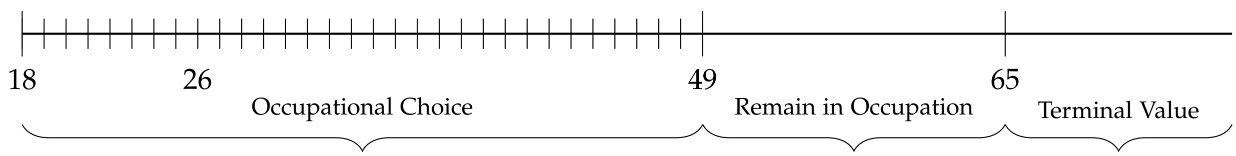
Appendix F Model Solution, Estimation, and Simulation

For replication, there are three main stages: 1) solution, 2) estimation, and 3) simulation.

Appendix F.1 Solution

Recall that agents make occupational choices from age 18 to 49 and from age 50 onward, we assume that they remain in the same occupation sector until the retirement age 65. Then, at age 65, the continuation value of retirement is normalized to zero. Figure A.6 shows the timeline.

Figure A.6: Model Timeline



In the data sample, less than 3% choose to attend school after the age of 25. Figure 1 shows that the share of schooling approaches near zero after the age of 25; therefore, we restrict schooling choice until age 25 to better fit our model. From age 27 to 49, agents choose among two alternatives: working and not working. The change in choices affects the following: i) the mental and physical health transition probability, ii) income, and iii) utility. Hence, we need to be careful doing backwards induction and computing the expected value functions. Below we describe the steps:

- At age 65, we obtain the expected value function for age 66, $\mathbb{E}[V_{66}(\mathbf{s}_{66}|\mathbf{s}_{65})] = 0$. This enters the continuation value for age 65 and we compute the expected value for age 65, $\mathbb{E}[V_{65}(\mathbf{s}_{65}|\mathbf{s}_{64})]$. To account for income shocks, we employ Monte Carlo integration, drawing 100 income shocks from a normal distribution and averaging them to estimate expected utility. For individuals not engaged in work, we incorporate the probability p_g^4 of receiving government allowances into the calculations. Since the agents' occupational choices at age 49 are unknown, we compute occupation-specific expected value functions for all possible scenarios (e.g., the agent remaining working or not working). This process is iteratively repeated for each preceding age until we reach age 50.

- At age 49, agents make the last occupational choice taking into account the choice-specific continuation values from $\mathbb{E}[V_{50}(\mathbf{s}_{50}|\mathbf{s}_{49})]$. Then, we compute the expected value function $\mathbb{E}[V_{49}(\mathbf{s}_{49}|\mathbf{s}_{48})]$, which follows the functional form à la Rust (1987). We no longer use choice-specific expected value functions but aggregate across all choices. We repeat this process until age 26.

- At age 25, agents have the last schooling option. Taking into account the expected value from age 26, $\mathbb{E}[V_{26}(\mathbf{s}_{26}|\mathbf{s}_{25})]$, we compute the expected value for age 25 $\mathbb{E}[V_{25}(\mathbf{s}_{25}|\mathbf{s}_{24})]$, which considers utility across three alternatives: schooling, working, and not working. We repeat this process until we reach initial age 18.

Appendix F.2 Estimation

We use the first stage estimates to solve for the second stage. From the optimization process above, we obtain the choice probabilities from ages 18 to 49. Moving into estimation, we will extract model solution for ages 18 to 41 to match our data sample. Given the characteristics of the data individual, we construct the maximum likelihood estimator using the choice probabilities from the model solution. Setting this as our objective function, we maximize our likelihood estimator (or minimize the negative likelihood).

Appendix F.3 Simulation

For model fit, we simulate forward the data individuals ($n \in \{1, ...N\}$) S times ($S = 1,000$) using our estimated parameters. The steps are described below:

1. Re-solve the model using estimated parameters. We store the state space and the expected value function (integrated out the income shocks) which will be used in the forward simulation.

2. Get individuals' initial conditions from the data: experience, education, age, mother's education, father's education, initial wealth. We exclude initial mental and physical health because we model these initial conditions with unobserved heterogeneity (Equation 23).

3. For each simulation of a given individual, start with initial age ($a_{n,1}$):

   (a) Determine individual type (Equation 21). Get the initial characteristics of the data individual (e.g. father's education, mother's education, age, and family wealth). Compute the type probabilities based on the characteristics. Generate a random number between 0 and 1 and determine the latent health type k_H.

   (b) Determine initial health using the probability of being in good health (Equation 23). In other words, generate a random number between 0 and 1; if it is less than the probability of having good initial health, the initial health is considered good.

   (c) Draw a preference shock from a standard T1EV distribution for each alternative.

   (d) Extract the corresponding expected value function (Equation 17) given the individual's state space variables and add the preference shock. Choose the alternative that yields the highest output.

   (e) Given choice, draw an income shock from the corresponding normal distribution and compute income (Equations 6, 7).

(f) Given choice, determine next period education and experience (Equations 8).

(g) Compute the life shock probability. Generate a random number between 0 and 1; if this number is smaller than the calculated probability, the individual experiences life shock the next period.

(h) Compute the mental health transition probability (Equation 13). Generate a random number between 0 and 1; if this number is smaller than the calculated probability, the individual is in good mental health the next period. We repeat for physical health and get next period physical health status.

(i) Repeat step (b) - (g) until the age we last observe the individual (a_{T_n}).

4. Repeat step 3. S times for all individuals.

5. Take the average across S and N.