

Disability, Labour Productivity and Lifetime Earnings: New Evidence from Australia

Man Hin Chio

Australian National University

Chung Tran

Australian National University

HILDA Conference, Oct 2026

People with disabilities in Australia

- In 2022, 5.5 million Australians (21.4% of the population) reported a disability, up from 4.4 million (18%) in 2018. (Australian Bureau of Statistics, 2024)

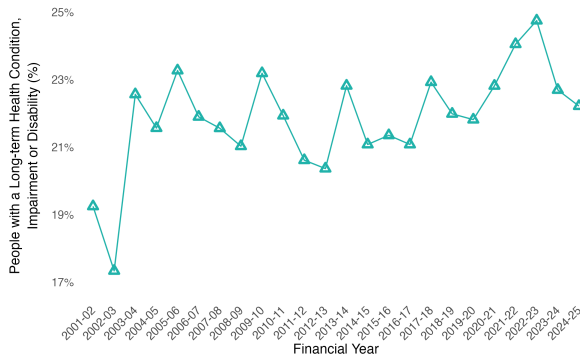


Figure: Share of the working-age population with a long-term health condition, impairment or disability (HILDA)

This paper

1. Estimates life-cycle profiles of labour productivity by education level and disability status
 - ▶ Using household survey data (HILDA)
 - ▶ Modeling heterogeneous labour inputs
2. Quantifies economic costs of disability
 - ▶ Using a structural model in which experience is accumulated endogenously through learning by doing

Main Results

1. Productivity gap associated with disability:
 - ▶ primarily lower labour efficiency
2. The experience component:
 - ▶ plays an increasing role over age
3. Removing the experience component (switching off learning by doing):
 - ▶ substantial loss in lifetime labour earnings, income and consumption

Part I: Empirical Analysis

Data

- ▶ The Household, Income and Labour Dynamics in Australia (HILDA): waves 1-24, 2001-2024
- ▶ Concept of disability:
 1. Non-disabled: no long-term health condition, impairment or disability, or a condition that does not limit work (limitation indicator 0)
 2. Disabled: long-term condition that limits the type or amount of work.
 - ▶ Moderate: limitation indicator between 1-5
 - ▶ Severe: limitation indicator between 6-10, or cannot work at all
- ▶ Concept of (work) experience: the total number of years an individual has been engaged in employment
- ▶ Other definitions:
 1. Education: non-university or university

Methodology

- ▶ Following Kim & Rhee (2022), we assume workers contribute two distinctive inputs:
 1. Pure labour: physical effort
 2. Pure experience: human capital accumulated through labour market participation
- ▶ The hourly wage rate, w , is used as a proxy for productivity.
- ▶ The wage equation can be written as

$$w(j, dis, e) = \underbrace{R_L \cdot \lambda_L(j, dis)}_{\text{Labour component}} + \underbrace{R_E \cdot \lambda_E(j, dis) \cdot g(e)}_{\text{Experience component}} \quad (1)$$

where j , dis , e , R , λ and $g(e)$ represent age, disability status, work experience, price, efficiency unit and a function of non-linear accumulated experience function.

Methodology

- ▶ Wages vary by education in the model. Equation (1) can be further rewritten as

$$w(j, dis, e, edu) = R_L \cdot \lambda_L(j, dis, edu) \times [1 + \Pi_E \cdot \frac{\lambda_E(j, dis, edu)}{\lambda_L(j, dis, edu)} \cdot g(e)], \quad (2)$$

where $\Pi_E \equiv R_E/R_L$ is the relative price of E to L .

- ▶ Finally, we estimate the log-wage transformation of (2):

$$\begin{aligned} \ln(w_{it}) = & d_t + \ln \phi_L(dis_{it}, edu_{it}) \\ & + [\lambda_{L,0}(edu_{it}) + \lambda_{L,1}(edu_{it})j_{it} + \lambda_{L,2}(edu_{it})j_{it}^2] \\ & + \ln \left[1 + \Pi_{E_t} \frac{\phi_E(dis_{it}, edu_{it})}{\phi_L(dis_{it}, edu_{it})} \right. \\ & \times \exp(\lambda_{E/L,0}(edu_{it}) + \lambda_{E/L,1}(edu_{it})j_{it} + \lambda_{E/L,2}(edu_{it})j_{it}^2) \\ & \left. \times (e_{it} + \gamma_1 e_{it}^2 + \gamma_2 e_{it}^3 + \gamma_3 e_{it}^4) \right] + \beta X_{it} + \epsilon_{it} \end{aligned} \quad (3)$$

Methodology

- ▶ Combining the estimated
 1. Efficiency schedules $\hat{\lambda}_L$ and $\hat{\lambda}_E$
 2. Accumulated experience $\hat{g}(e)$
 3. Relative price $\hat{\Pi}_E$
 4. Other regressors $\hat{z}$,

total productivity can be decomposed into two components, the labour component and the experience component.

- ▶ Equation (2) can be expressed as

$$\hat{w}_{it}(j, dis, e, edu) = \hat{z}_{it} \cdot \hat{R}_{L_t} \cdot \hat{\lambda}_L(j, dis, edu) \cdot [1 + \hat{\Pi}_E \cdot \frac{\hat{\lambda}_E(j, dis, edu)}{\hat{\lambda}_L(j, dis, edu)} \cdot \hat{g}(e)], \quad (4)$$

where $\hat{z}_{it} \cdot \hat{R}_{L_t} \cdot \hat{\lambda}_L(j, dis, edu)$ is denoted as the base wage or the labour component, and $\hat{z}_{it} \cdot \hat{R}_{E_t} \cdot \hat{\lambda}_E(j, dis, edu) \cdot \hat{g}(e)$ is defined as the experience component.

Identification

- ▶ Wages are observed only for employed workers, leading to selection bias when estimating Equation (3).
- ▶ Two-stage estimation procedure proposed by Heckman (1979):

1. First stage:

$$\text{Probability}(emp_{it} = 1 | X_{it}, Z_{it}) = \Lambda(X_{it}, Z_{it}), \quad (5)$$

where Z is the instrument.

2. Second stage: Obtain the inverse Mills ratio and include it in Equation (3).
- ▶ We use the one-year lagged weekly time spent on household errands as the instrument:
 1. Relevance: Wald test and partial F statistic in the selection equation
 2. Exclusion: reduced-form falsification diagnostic

First stage regression results

Variable	Coefficient	Effect on the Probability	
		Average Marginal Effect	Marginal Effect at the Mean
<i>Disability Status</i>			
Moderately Disabled	-0.3340*** (0.0177)	-0.1055 (0.0055)	-0.1313 (0.0070)
Severely Disabled	-0.9718*** (0.0232)	-0.3069 (0.0071)	-0.3676 (0.0076)
<i>Instrument</i>			
Lagged Household Errands	-0.0228*** (0.0012)	-0.0072 (0.0004)	-0.0087 (0.0005)
Sample Size	168,515	McFadden Pseudo R^2	0.1414

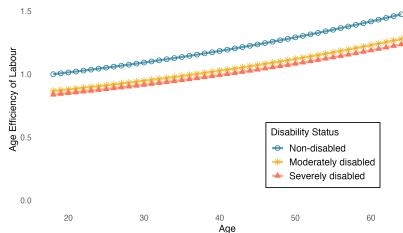
- ▶ Moderate (severe) disability is associated with a 10.55 (30.69) percentage point lower probability.
- ▶ Significance levels are denoted as follows:
* * * $p < 0.001$, * * $p < 0.01$, * $p < 0.05$.

Second stage regression results

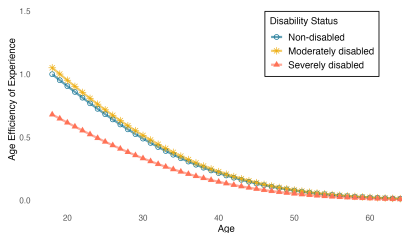
Labour			Disability		
<i>Non-university</i>			<i>Non-university</i>		
$\lambda_{L,1}$	0.0070	(0.0046)	$\ln \phi_L(MD, LE)$	-0.1419**	(0.0447)
$\lambda_{L,2}$	0.0000	(0.0001)	$\ln \phi_L(SD, LE)$	-0.1763*	(0.0724)
<i>University</i>			<i>University</i>		
$\lambda_{L,0}$	0.1884***	(0.0321)	$\ln \phi_L(MD, HE)$	-0.1127	(0.0586)
$\lambda_{L,1}$	0.0206***	(0.0050)	$\ln \phi_L(SD, HE)$	-0.1846*	(0.0893)
$\lambda_{L,2}$	-0.0002*	(0.0001)	Accumulated Experience		
Experience			γ_1	0.0496	(0.0512)
<i>Non-university</i>			γ_2	-0.0030	(0.0027)
$\lambda_{E,1}$	-0.0474*	(0.0223)	γ_3	0.0001	(0.0001)
$\lambda_{E,2}$	-0.0010*	(0.0004)	Relative Efficiency of E to L		
<i>University</i>			<i>Non-university</i>		
$\lambda_{E,0}$	-0.6294**	(0.2145)	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2114***	(0.1528)
$\lambda_{E,1}$	0.0288	(0.0262)	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8118**	(0.2555)
$\lambda_{E,2}$	-0.0025***	(0.0006)	<i>University</i>		
Inverse Mills Ratio			$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1847***	(0.2811)
0.0674	(0.0544)		$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0376**	(0.4002)
Sample Size			Weighted R^2	0.2708	
108,702					

- Moderate and severe disabilities reduce labour efficiency by 11.9% and 16.5% on average. Severe disability also reduces experience efficiency (by 32.0% for non-university workers).

Life-cycle profiles of efficiencies: Non-university cohort



(a) Labour efficiency



(b) Experience efficiency

Figure: Life-cycle patterns of labour [λ_L] and experience [λ_E] efficiencies

Accumulated Experience

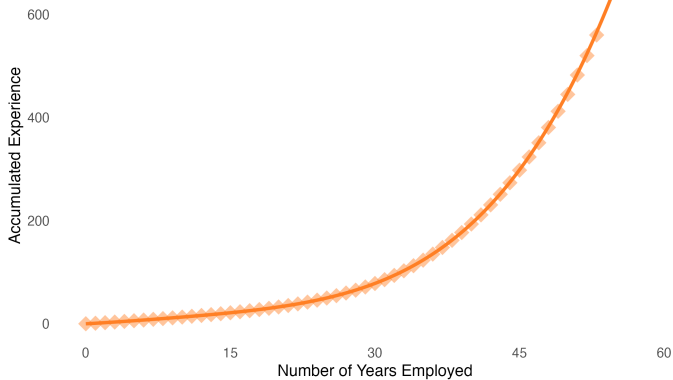


Figure: Cumulative experience function $[g(e)]$

Life-cycle profiles of effective experience: Non-university cohort

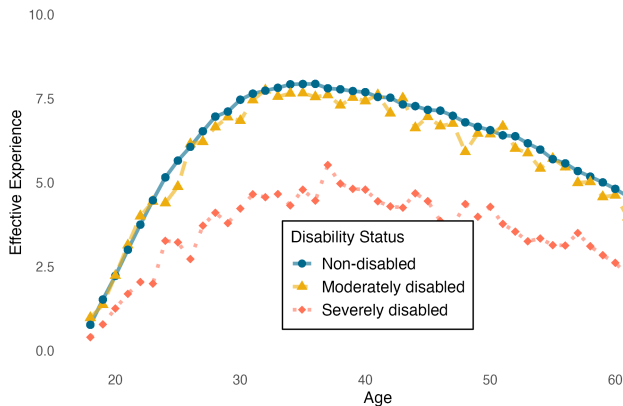
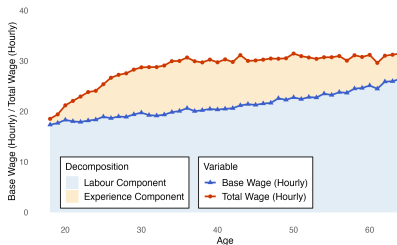


Figure: Life-cycle patterns of effective experience $[\lambda_E \times g(e)]$

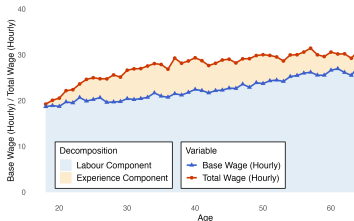
life-cycle profiles of predicted productivity : Non-university cohort



(a) Non-disabled



(b) Moderately disabled



(c) Severely disabled

Part II: Structural Analysis

Stochastic Overlapping Generations Model

- ▶ Disability type: $\varepsilon_D \in \{\text{ND}, \text{MD}, \text{SD}\}$
(Non-disabled, Moderately disabled, Severely disabled)
- ▶ Education type: $\varepsilon_E \in \{\text{NU}, \text{U}\}$
(Non-university, University)
- ▶ Labour productivity shock: $\eta_z \in \{\eta_{\text{Low}}, \eta_{\text{Mid}}, \eta_{\text{High}}\}$, with transition probability matrix $\pi_z(\eta_{z,j+1}|\eta_{z,j})$
- ▶ Endogenous experience: x_j , accumulated through learning by doing
- ▶ Calibration:
 1. Australian tax and transfer system (progressive tax, age pension, disability support pension)
 2. Learning-by-doing technology disciplined by the estimated experience component

Endogenous experience: learning by doing

- ▶ In the model, experience x_j is a state variable accumulated endogenously from weekly hours worked h_j :

$$x_{j+1} = (1 - \delta_x) x_j + \min \left\{ 1, \left(\frac{h_j}{40} \right)^{\eta_x} \right\} \quad (6)$$

full-time work adds at most one FTE year per period; experience depreciates at rate δ_x

- ▶ Experience raises hourly productivity through the bounded learning function

$$g_{\varepsilon_D, \varepsilon_E}(x_j) = 1 + \kappa_x(\varepsilon_D, \varepsilon_E) (1 - e^{-\theta_x x_j}) \quad (7)$$

- ▶ Labour income: $\eta(z_j) \bar{e}_{j, \varepsilon_D, \varepsilon_E} g_{\varepsilon_D, \varepsilon_E}(x_j) (1 - l_j) w$
- ▶ $\kappa_x(\varepsilon_D, \varepsilon_E)$: calibrated to the estimated experience premium of each group; hours today raise productivity tomorrow

Household problem

$$V_j(\chi_j) = \max_{c_j, l_j, a_{j+1}} \left\{ u(c_j, l_j; \bar{n}_{j, \varepsilon_D, \varepsilon_E} \cdot 1_{[0 < n_j]}) + \right. \\ \left. \beta \left[\psi_{j+1} \sum_{\eta_{z,j+1}} \pi_z(\eta_{z,j+1} | \eta_{z,j}) \cdot V_{j+1}(\chi_{j+1}) + \right. \right. \\ \left. \left. (1 - \psi_{j+1}) b(a_j) \right] \right\}, \quad (8)$$

subject to

$$a_{j+1} = \underbrace{ra_j + \eta_{z,j} e_{j, \varepsilon_D, \varepsilon_E} g_{\varepsilon_D, \varepsilon_E}(x_j) (1 - l_j) w}_{\text{Market income}(y_j^m)} + \text{pension}_{j \geq J^p} \quad (9)$$

$$+ \text{dsp}_{j < J^p} - \text{tax}(y_j) + \text{beq}_j + a_j - (1 + \tau_c) c_j$$

and the experience accumulation rule.

Calibration

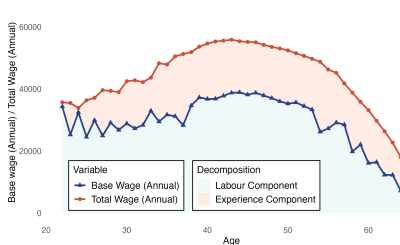
Parameter description	Parameter value	Source/Target
<i>Demographics and Preferences</i>		
Number of periods	$J = 69$	---
Retirement age	$J_w = 44$	---
Population growth rate	$n = 1.4\%$	ABS
Survival rates	ψ_j	ABS 2015-2017 Life Tables
Relative risk aversion	$\sigma = 3.694$	Life-cycle labour supply
Weight of consumption	$\gamma = 0.344$	Life-cycle labour supply
Discount factor	$\beta = 0.996$	Standard value
<i>Technology and Market Structure</i>		
Capital share of output	$\alpha = 0.35$	Tran and Woodland (2014)
GDP per capita growth rate	$g = 1.6\%$	Kudrna et al. (2022)
Depreciation rate	$\delta = 0.05$	Tran and Woodland (2014)
Total factor productivity	$A = 1$	Tran and Woodland (2014)
Interest rate	$r = 2\%$	Standard SOE calibration
<i>Bequest</i>		
Motive intensity	$\phi_1 = -0.5$	De Nardi (2004)
Degree of luxury	$\phi_2 = 11.6$	De Nardi (2004)
<i>Endowments and Learning by Doing</i>		
Deterministic labour productivity (labour-only)	$\bar{\varepsilon}_{j,\varepsilon_D,\varepsilon_E}$	Empirical analysis
Shock: persistence	$\rho = 0.8081$	HILDA wage residuals
Shock: innovation variance	$\sigma_\eta^2 = 0.0134$	HILDA wage residuals
Shock: realised productivity	$\eta(\varepsilon_j) = \{0.729, 0.979, 1.315\}$	Tauchen discretisation of the estimated process
Wage rate	$w = 1.5463$	---
Labour force participation cost	$\theta_{j,\varepsilon_D,\varepsilon_E}$	Life-cycle labour supply
Work-hour disutility multipliers	m_h	Life-cycle labour hours
Work-cost knots (ages 22, 43, 64)	$\kappa_j(\varepsilon_E, \varepsilon_D)$	Life-cycle employment and hours
Severe-disability work-cost level	$\kappa_D = 0.05$	DSP recipient ratio
Severe-disability work-cost slope	$\kappa_{D,age} = 0.10$	DSP recipient ratio
Experience gains, non-university	$\kappa_N = \{0.58, 0.82, 1.07\}$	Estimated experience premium
Experience gains, university	$\kappa_U = \{0.41, 0.50, 0.58\}$	Estimated experience premium
Learning curvature	$\theta_E = 0.049$	Benchmark value
Experience depreciation	$\delta_E = 0.010$	Benchmark value
Hours-to-experience elasticity	$\eta_E = 0.948$	Benchmark value

Parameter description	Parameter value	Source/Target
<i>Initial distributions</i>		
Education	$\mu_{j=1}^E = \{0.81, 0.19\}$	HILDA
Disability	$\mu_{j=1}^D = \{0.92, 0.05, 0.03\}$	HILDA
Assets	$\mu_{j=1}^A$	HILDA
Joint distributions	$\mu_{j,\varepsilon_E,\varepsilon_D}^E$	HILDA
<i>Tax and transfer</i>		
Consumption tax	$\tau_c = 10\%$	ATO
Income tax: curvature	$\tau_y = 0.15$	Tran and Zakariyya (2022)
Income tax: scaling	$\lambda = 0.5962$	---
Government expenditure share	$G/Y = 0.229$	IMF WEO
Government bond share	$B/Y = 0.186$	IMF WEO
Income test taper rate	$\omega^0 = 0.5$	Services Australia (2018 rates)
Assets test taper rate	$\omega^0 = 0.003$	Services Australia (2018 rates)
Maximum pension (in model unit)	$p^{\max} = 0.0421$	Services Australia (2018 rates)
Lower income threshold (in model unit)	$\bar{y}_1 = 0.0087$	Services Australia (2018 rates)
Lower assets threshold (in model unit)	$\bar{a}_1 = 0.5013$	Services Australia (2018 rates)
Hours threshold	$\bar{h} = 15$	Services Australia (2018 rates)
DSP income test taper rate	$\omega_D^0 = 0.5$	Services Australia (2018 rates)
DSP assets test taper rate	$\omega_D^0 = 0.003$	Services Australia (2018 rates)
Maximum DSP (in model unit)	$d^{\max} = 0.0063$	Services Australia (2018 rates)
DSP lower income threshold	$\bar{y}_D = 0.0013$	Services Australia (2018 rates)
DSP lower assets threshold	$\bar{a}_D = 0.0752$	Services Australia (2018 rates)
DSP hours threshold	$\bar{h}_D = 15$	Services Australia (2018 rates)
DSP schedule multiplier	$s_D = 0.15$	DSP recipient ratio
DSP eligible disability state	$\varepsilon_D = SD$	Assumed medical test

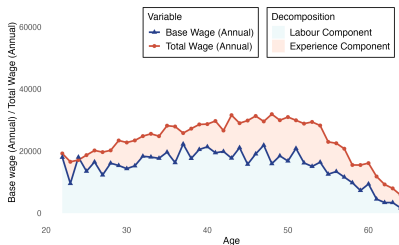
Experiment

- ▶ To what extent would the **removal of the experience component** reduce lifetime (life-cycle) labour earnings, net income and consumption? Would the effect vary across education and disability?
- ▶ Implementation: switch off the learning-by-doing channel ($\kappa_x = 0$, so $g(x) = 1$), holding prices at the benchmark.

life-cycle profiles of labour earnings : Non-university cohort



(a) Non-disabled



(b) Moderately disabled



(c) Severely disabled

Experiment results: Removal of experience component

	(1) Benchmark (\$)			(2) Remove Experience Component (%Δ)		
	<i>Labour Income</i>	<i>Net Income</i>	<i>Consumption</i>	<i>Labour Income</i>	<i>Net Income</i>	<i>Consumption</i>
Non-university						
Non-disabled	1,278,868	973,951	812,231	-32.25%	-28.38%	-28.55%
Moderately Disabled	677,696	563,700	479,769	-33.57%	-28.24%	-27.99%
Severely Disabled	183,846	222,328	192,822	-24.51%	-14.77%	-14.76%
University						
Non-disabled	1,972,446	1,402,538	1,146,349	-24.80%	-21.86%	-22.58%
Moderately Disabled	1,476,734	1,096,580	904,148	-29.18%	-25.79%	-26.10%
Severely Disabled	806,684	653,775	541,823	-26.45%	-22.16%	-22.02%

Figure: Removal of experience component:
Lifetime labour income, net income and consumption

Conclusion

- ▶ Address the gap in Australian literature by exploring disability effects on heterogeneous human capital
- ▶ We find that
 1. Disability-related productivity gaps are mainly driven by lower labour efficiency.
 2. Experience matters for non-university workers.
 3. Removing the experience component significantly reduces income (monetary) and consumption (welfare).
- ▶ Next steps...
 1. General equilibrium model with stochastic disability shocks
 2. Evaluate DSP policy reforms

Extension: Elasticity of substitution

Aggregate economy

- ▶ Assume a representative firm in an aggregate economy, who exhibits a CES production function:

$$Y_t = A_t F(L_t, E_t) = A_t (L_t^\zeta + \delta E_t^\zeta)^{\frac{1}{\zeta}}, \quad (10)$$

where δ captures the relative efficiency of E to L , and ζ determines the substitutability between the inputs.

- ▶ The elasticity of substitution between labour L and experience E is given by $\frac{1}{1-\zeta}$:
 1. If $\zeta = 1$, labour and experience are perfect substitutes
 2. If $\zeta < 1$, they are imperfect substitutes or complements: their relative prices are affected by their relative proportions

Relative price of experience to labour

- ▶ Following Kim & Rhee (2022), we compute aggregate labour and experience by summing individuals at time t :

$$\hat{L}_t = \sum_i \hat{\lambda}_L(j, dis, edu) \cdot h_{it} \quad (11)$$

$$\hat{E}_t = \sum_i \hat{\lambda}_E(j, dis, edu) \cdot \hat{g}(e) \cdot h_{it} \quad (12)$$

- ▶ Relative supply of E to L : $\hat{E}_t / \hat{L}_t$.
- ▶ Relative price of E to $L = \Pi_{E_t} \equiv \frac{F_{E_t}}{F_{L_t}}$, where F is the marginal product.
- ▶ With the CES form, relative price can be written as

$$\Pi_{E_t} = \delta \left(\frac{E_t}{L_t} \right)^{\zeta-1} \quad (13)$$

Estimation of δ and ζ



- ▶ The elasticity of substitution is **not identified** in this sample: only one of four specifications yields an admissible (negative) slope, and none is robustly significant.
- ▶ Nothing in the structural model depends on this elasticity: production is Cobb–Douglas in capital and effective labour.

CES price regression across specifications

Specification	Slope on $\ln(E_t/L_t)$	OLS SE	Newey-West SE	Bootstrap SE	Implied σ
Simple (Kim-Rhee)	0.2206	(0.4489)	(0.6009)	[1.0627]	- - -
Linear trend	-6.3233	(3.2697)	(2.9435)	[3.4419]	0.158
Quadratic trend	3.6506	(4.5106)	(3.7821)	[3.6046]	- - -
First differences	1.1153	(3.6253)	(2.6443)	[3.7644]	- - -
Waves (levels / first differences)	22 / 21				

References I

- Australian Bureau of Statistics. (2024). Disability, ageing and carers, australia: Summary of findings, 2022. (ABS Catalogue No. 4430.0)
- Cai, L. (2009). Effects of health on wages of australian men. *Economic record*, 85(270), 290–306.
- Cai, L. (2021). The effects of health on the wages of australian workers: gender differences and the impacts of macroeconomic conditions. *International Journal of Manpower*, 42(5), 842–865.
- Cai, L., & Jeffrey Waddoups, C. (2012). Unobserved heterogeneity, job training and the employer size–wage effect in australia. *Australian Economic Review*, 45(2), 158–175.
- Card, D., & Lemieux, T. (2001). Can falling supply explain the rising return to college for younger men? a cohort-based analysis. *The quarterly journal of economics*, 116(2), 705–746.

References II

- Deshpande, M., Kaplan, G., & Leigh-Wood, T. (2025). *Evaluating recent crackdowns on disability benefits: Effects on income and health care use in australia* (Tech. Rep.). National Bureau of Economic Research.
- Fox, J. T., & Smeets, V. (2011). Does input quality drive measured differences in firm productivity? *International Economic Review*, 52(4), 961–989.
- Gilleskie, D., & Hoffman, D. (2014). Health capital and human capital as explanations for health-related wage disparities. *Journal of Human Capital*, 8(3), 235–279.
- Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153–161.
- Jeong, H., Kim, Y., & Manovskii, I. (2015). The price of experience. *American Economic Review*, 105(2), 784–815.

References III

- Jung, J., & Tran, C. (2022). Social health insurance: A quantitative exploration. *Journal of Economic Dynamics and Control*, 139, 104374.
- Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963-1987: supply and demand factors. *The quarterly journal of economics*, 107(1), 35–78.
- Keane, M. P. (2016). Life-cycle labour supply with human capital: econometric and behavioural implications. *The Economic Journal*, 126(592), 546–577.
- Kim, S., & Rhee, S. (2022). Understanding the aggregate effects of disability insurance. *Review of Economic Dynamics*, 46, 328–364.
- Kitao, S. (2014). A life-cycle model of unemployment and disability insurance. *Journal of Monetary Economics*, 68, 1–18.

References IV

- Kudrna, G., Tran, C., & Woodland, A. (2022). Sustainable and equitable pensions with means testing in aging economies. *European Economic Review*, 141, 103947.
- Low, H., & Pistaferri, L. (2015). Disability insurance and the dynamics of the incentive insurance trade-off. *American Economic Review*, 105(10), 2986–3029.
- Michaud, A., & Wiczer, D. (2021). The disability option: Labor market dynamics with macroeconomic and health risks. (CHCP Working Paper)
- Tran, C., & Zakariyya, N. (2022). Progressive pension and optimal tax progressivity.
- Wilkins, R. (2004). The effects of disability on labour force status in australia. *Australian Economic Review*, 37(4), 359–382.

Appendix

Related literature

► Empirical work:

1. Heterogeneous production inputs:
Katz & Murphy (1992); Card & Lemieux (2001); Fox & Smeets (2011)
2. Labour supply and human capital:
Jeong, Kim, & Manovskii (2015); Keane (2016)
3. Disability effects:
Gilleskie & Hoffman (2014); Kim & Rhee (2022)

► Structural model:

Kitao (2014); Low & Pistaferri (2015); Michaud & Wiczer (2021); Kim & Rhee (2022); Jung & Tran (2022)

► Australian literature:

Wilkins (2004); Cai (2009); Cai & Jeffrey Waddoups (2012); Cai (2021); Deshpande, Kaplan, & Leigh-Wood (2025)

Sample size

Age Range	(1) Disability			(2) Education	
	<i>Non-disabled</i>	<i>Moderately Disabled</i>	<i>Severely Disabled</i>	<i>Non-university</i>	<i>University</i>
18-27	56,905	3,311	1,983	51,172	11,112
28-37	56,730	3,628	2,638	40,736	22,304
38-47	51,348	4,304	3,900	39,970	19,630
48-57	44,556	5,594	6,000	40,213	15,982
58-64	23,608	4,604	5,534	25,507	8,262

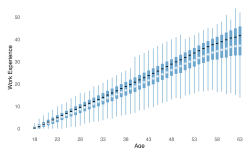
Summary statistics by age

<i>Variable</i>	<i>Age Range</i>				
	18-27	28-37	38-47	48-57	58-64
Ratio (%)	22.29	22.68	22.00	20.86	12.17
Male (%)	50.79 (0.50)	49.44 (0.50)	49.23 (0.50)	49.01 (0.50)	49.36 (0.50)
Married (%)	26.75 (0.44)	69.45 (0.46)	76.07 (0.43)	75.47 (0.43)	74.35 (0.44)
University (%)	20.03 (0.40)	38.35 (0.49)	33.62 (0.47)	28.21 (0.45)	22.86 (0.42)
Employed (%)	76.48 (0.42)	80.21 (0.40)	82.59 (0.38)	77.54 (0.42)	53.41 (0.50)
Disabled (%)	7.93 (0.27)	9.36 (0.29)	13.48 (0.34)	20.42 (0.40)	31.07 (0.46)
Work Experience	3.67 (2.92)	11.22 (4.89)	19.80 (6.85)	28.41 (8.91)	34.12 (11.33)
Working Hours	1741.33 (738.58)	2037.68 (692.64)	2035.65 (714.28)	2044.34 (715.17)	1866.55 (792.91)
Limitation Score	0.41 (1.54)	0.51 (1.75)	0.77 (2.17)	1.22 (2.66)	1.92 (3.18)
Years of Schooling	11.07 (1.05)	11.03 (1.19)	10.75 (1.34)	10.45 (1.43)	10.15 (1.59)

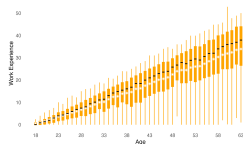
Summary statistics by disability and education

<i>Variable</i>	Non-disabled	Moderately disabled	Severely disabled	Non-university	University
Age	38.97 (12.90)	44.92 (13.29)	48.00 (12.47)	39.95 (13.82)	40.42 (11.51)
Male (%)	50.14 (0.50)	44.77 (0.50)	48.08 (0.50)	51.40 (0.50)	45.23 (0.50)
Married (%)	64.48 (0.48)	59.37 (0.49)	53.44 (0.50)	59.23 (0.49)	73.01 (0.44)
University (%)	31.42 (0.46)	21.30 (0.41)	12.32 (0.33)	- - -	- - -
Employed (%)	82.20 (0.38)	58.10 (0.49)	25.06 (0.43)	72.00 (0.45)	86.04 (0.35)
Disabled (%)	- - -	- - -	- - -	16.39 (0.37)	8.28 (0.28)
Work Experience	17.69 (12.59)	20.08 (13.23)	18.91 (13.33)	18.02 (13.25)	17.80 (11.30)
Working Hours	1976.95 (721.75)	1817.11 (790.31)	1562.25 (847.92)	1774.69 (703.27)	2001.34 (666.33)
Limitation Score	0.00 (0.00)	3.67 (1.28)	7.88 (1.46)	5.63 (2.38)	4.67 (2.44)
Years of Schooling	10.85 (1.26)	10.36 (1.51)	9.97 (1.70)	10.46 (1.40)	11.46 (0.86)

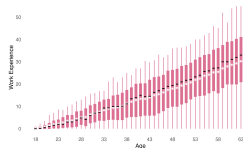
Distribution of work experience by disability status and education



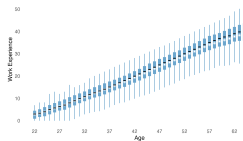
(a) Non-university, ND



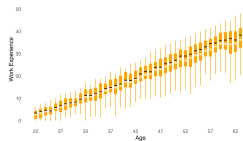
(b) Non-university, MD



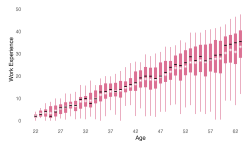
(c) Non-university, SD



(d) University, ND



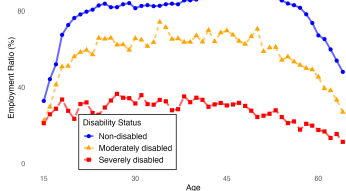
(e) University, MD



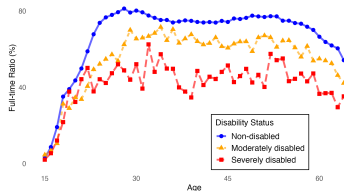
(f) University, SD

Disability and employment

- ▶ Non-employment is prevalent among people with disabilities.
- ▶ They are less likely to work full-time compared to those without disabilities.



(a) Employment Ratio



(b) Full-time Ratio

Figure: Life-cycle patterns of employment and full-time status by disability status

Disability and education

- ▶ Only 20% of individuals with moderate disabilities and 10% of those with severe disabilities have attained a university degree.

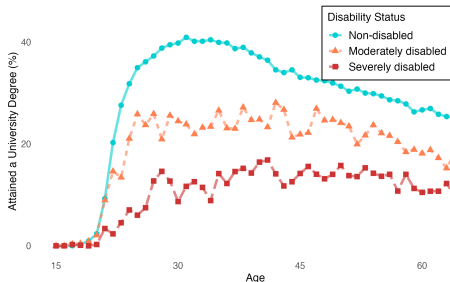


Figure: Life-cycle patterns of university education attainment by disability status

Instrument relevance and exclusion diagnostics

	<i>(i) Relevance</i>		<i>(ii) Exclusion diagnostic</i>	
χ^2	374.66***	607.83***	0.01	1.05
p-value	0.0000	0.0000	0.9062	0.5907
Lagged Household Errands	✓	✓	✓	✓
Current Household Errands		✓		✓
Sample Size	168,515	155,657	108,702	101,005

Exclusion restriction: other candidates

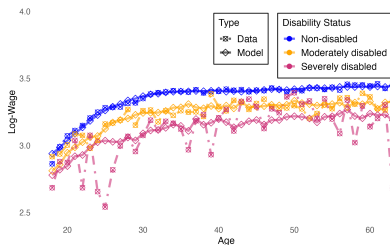
Candidate	Relevance: Wald	Relevance: partial F	Exclusion: Wald	Exclusion: p-value	Passes screen
Errands, lagged one wave	374.66***	446.66	0.01	0.9062	yes
Errands, lagged two waves	221.65***	272.43	0.73	0.3942	yes
Errands, current wave	720.37***	883.34	0.03	0.8636	yes
Outdoor tasks, lagged	183.28***	205.53	0.22	0.6376	yes
Housework, lagged	453.46***	582.02	2.96	0.0853	no
Child care, lagged	936.68***	986.11	1.62	0.2036	yes
Care of other children, lagged	30.76***	36.13	9.71**	0.0018	no
Volunteering, lagged	47.47***	59.23	10.77**	0.0010	no
Care of an adult, lagged	108.86***	99.26	2.14	0.1439	yes

First stage probit regression results

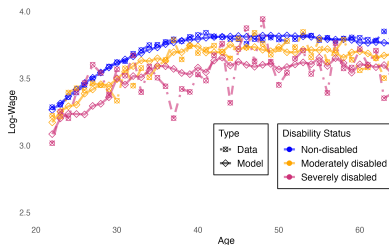
Variable	Coefficient	
Moderately Disabled	-0.3340***	(0.0177)
Severely Disabled	-0.9718***	(0.0232)
Age	-0.0661***	(0.0031)
Age ²	0.0000	(0.0001)
Experience	0.1630***	(0.0048)
Experience ²	-0.0035***	(0.0002)
Experience ³	0.0000***	(0.0000)
Married	-0.0925***	(0.0144)
Male	-0.0188	(0.0138)
University	0.2507***	(0.0161)
Sample Size	168,515	
Pseudo R^2	0.1414	

Variable	Coefficient	
A/TS Islander Status	-0.1134**	(0.0382)
State		
VIC	-0.0742***	(0.0182)
QLD	-0.0518**	(0.0194)
SA	-0.0094	(0.0277)
WA	-0.0033	(0.0272)
TAS	0.1354***	(0.0383)
NT	0.0105	(0.0660)
ACT	0.0487	(0.0419)
Lagged Household Errands	-0.0228***	(0.0012)

Data VS Model: log-wage trends



(a) Non-university



(b) University

Second stage robustness check: Selection control

Coefficients		(1) With Selection Control	(2) Without Selection Control
Labour			
Non-university	$\lambda_{L,1}$	0.0070 (0.0046)	0.0092** (0.0033)
	$\lambda_{L,2}$	0.0000 (0.0001)	-0.0000 (0.0001)
University	$\lambda_{L,0}$	0.1884*** (0.0321)	0.1869*** (0.0306)
	$\lambda_{L,1}$	0.0206*** (0.0050)	0.0215*** (0.0043)
	$\lambda_{L,2}$	-0.0002* (0.0001)	-0.0002* (0.0001)
Experience			
Non-university	$\lambda_{E,1}$	-0.0474* (0.0223)	-0.0483* (0.0237)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0011* (0.0005)
University	$\lambda_{E,0}$	-0.6294** (0.2145)	-0.8003*** (0.2260)
	$\lambda_{E,1}$	0.0288 (0.0262)	0.0460 (0.0284)
	$\lambda_{E,2}$	-0.0025*** (0.0006)	-0.0030*** (0.0007)
Inverse Mills Ratio		0.0674 (0.0544)	- - -
Disability			
Non-university	$\ln \phi_L(MD, LE)$	-0.1419** (0.0447)	-0.1218*** (0.0361)
	$\ln \phi_L(SD, LE)$	-0.1763* (0.0724)	-0.1203 (0.0636)
University	$\ln \phi_L(MD, HE)$	-0.1127 (0.0586)	-0.0875 (0.0504)
	$\ln \phi_L(SD, HE)$	-0.1846* (0.0893)	-0.1357 (0.0717)
Accumulated Experience			
γ_1		0.0496 (0.0512)	0.0613 (0.0605)
γ_2		-0.0030 (0.0027)	-0.0042 (0.0035)
γ_3		0.0001 (0.0001)	0.0001 (0.0001)
Relative Efficiency of E to L			
Non-university	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2114*** (0.1528)	1.2041*** (0.1635)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8118** (0.2555)	0.7065* (0.2761)
University	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1847*** (0.2811)	1.1269*** (0.2806)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0376** (0.4002)	0.9777* (0.4059)
Sample Size		108,702	108,702
Weighted R^2		0.2708	0.2707

Second stage robustness check: Alternative specification

Coefficients		(1) Benchmark	(2)	(3)	(4)
Labour					
Non-university	$\lambda_{L,1}$	0.0070 (0.0046)	0.0115** (0.0039)	0.0070 (0.0046)	0.0064 (0.0050)
	$\lambda_{L,2}$	0.0000 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
University	$\lambda_{L,0}$	0.1884*** (0.0321)	0.2248*** (0.0377)	0.1881*** (0.0321)	0.2990*** (0.0111)
	$\lambda_{L,1}$	0.0206*** (0.0050)	0.0052 (0.0079)	0.0208*** (0.0049)	---
	$\lambda_{L,2}$	-0.0002* (0.0001)	0.0001 (0.0002)	-0.0002* (0.0001)	---
Experience					
Non-university	$\lambda_{E,1}$	-0.0474* (0.0223)	-0.1062*** (0.0322)	-0.0472* (0.0224)	-0.0358 (0.0239)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0002 (0.0006)	-0.0010* (0.0004)	-0.0008 (0.0005)
University	$\lambda_{E,0}$	-0.6294** (0.2145)	-0.1938 (0.3460)	-0.6268** (0.2161)	---
	$\lambda_{E,1}$	0.0288 (0.0262)	0.0720** (0.0247)	0.0285 (0.0262)	---
	$\lambda_{E,2}$	-0.0025*** (0.0006)	-0.0024*** (0.0005)	-0.0025*** (0.0006)	---
Inverse Mills Ratio		0.0674 (0.0544)	0.0729 (0.0532)	0.0638 (0.0540)	0.0739 (0.0558)
Disability					
Non-university	$\ln \phi_L(MD, LE)$	-0.1419** (0.0447)	-0.1445*** (0.0428)	-0.1288*** (0.0370)	-0.1282** (0.0441)
	$\ln \phi_L(SD, LE)$	-0.1763* (0.0724)	-0.1849*** (0.0669)	-0.1688** (0.0615)	-0.1906* (0.0809)
University	$\ln \phi_L(MD, HE)$	-0.1127 (0.0586)	-0.1230 (0.0750)	---	-0.1646* (0.0818)
	$\ln \phi_L(SD, HE)$	-0.1846* (0.0893)	-0.1008 (0.1089)	---	-0.1590 (0.1139)
Accumulated Experience					
Non-university	$\gamma_1(LE)$	0.0496 (0.0512)	0.1967 (0.1518)	0.0509 (0.0524)	0.0505 (0.0489)
	$\gamma_2(LE)$	-0.0030 (0.0027)	-0.0081 (0.0080)	-0.0031 (0.0028)	-0.0019 (0.0018)
	$\gamma_3(LE)$	0.0001 (0.0001)	0.0003 (0.0003)	0.0001 (0.0001)	0.0001 (0.0000)
	$\gamma_1(HE)$	---	-0.0069 (0.0327)	---	---
University	$\gamma_2(HE)$	---	-0.0010 (0.0017)	---	---
	$\gamma_3(HE)$	---	0.0000 (0.0000)	---	---
Relative Efficiency of E to L					
Non-university	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2114*** (0.1528)	1.2513*** (0.1613)	1.1841*** (0.1296)	1.1141*** (0.1459)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8118** (0.2555)	0.8167** (0.2622)	0.8184*** (0.2225)	0.8503** (0.2673)
University	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1847*** (0.2811)	1.1570*** (0.2456)	---	1.4248*** (0.3501)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0376** (0.4002)	0.7453* (0.3163)	---	0.9854* (0.4233)
Education-dependent Terms					
λ_L and λ_E		✓	✓	✓	
ϕ_L and ϕ_E		✓	✓		✓
$g(e)$			✓		
Sample Size		108,702	108,702	108,702	108,702
Weighted R^2		0.2708	0.2715	0.2707	0.2668

Second stage robustness check: Alternative variance estimators

Coefficients		(1) Benchmark	(2)	(3)	(4)
Labour					
Non-university	$\lambda_{L,1}$	0.0070 (0.0046)	0.0070* (0.0028)	0.0070 (0.0046)	0.0070 (0.0057)
	$\lambda_{L,2}$	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
University	$\lambda_{L,0}$	0.1884*** (0.0321)	0.1884*** (0.0252)	0.1884*** (0.0329)	0.1884*** (0.0569)
	$\lambda_{L,1}$	0.0206*** (0.0050)	0.0206*** (0.0033)	0.0206*** (0.0048)	0.0206 (0.0137)
	$\lambda_{L,2}$	-0.0002* (0.0001)	-0.0002** (0.0001)	-0.0002* (0.0001)	-0.0002 (0.0004)
Experience					
Non-university	$\lambda_{E,1}$	-0.0474* (0.0223)	-0.0474*** (0.0142)	-0.0474* (0.0226)	-0.0474 (0.0645)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0010*** (0.0003)	-0.0010* (0.0004)	-0.0010 (0.0013)
University	$\lambda_{E,0}$	-0.6294** (0.2145)	-0.6294*** (0.1453)	-0.6294** (0.2041)	-0.6294 (0.3630)
	$\lambda_{E,1}$	0.0288 (0.0262)	0.0288 (0.0170)	0.0288 (0.0250)	0.0288 (0.0950)
	$\lambda_{E,2}$	-0.0025*** (0.0006)	-0.0025*** (0.0004)	-0.0025*** (0.0006)	-0.0025 (0.0023)
Inverse Mills Ratio		0.0674 (0.0544)	0.0674* (0.0326)	0.0674 (0.0491)	0.0674 (0.0760)
Disability					
Non-university	$\ln \phi_L(MD, LE)$	-0.1419** (0.0447)	-0.1419*** (0.0299)	-0.1419** (0.0495)	-0.1419** (0.0460)
	$\ln \phi_L(SD, LE)$	-0.1763* (0.0724)	-0.1763** (0.0537)	-0.1763** (0.0605)	-0.1763 (0.1317)
University	$\ln \phi_L(MD, HE)$	-0.1127 (0.0586)	-0.1127** (0.0406)	-0.1127* (0.0561)	-0.1127 (0.0627)
	$\ln \phi_L(SD, HE)$	-0.1846* (0.0893)	-0.1846** (0.0680)	-0.1846* (0.0893)	-0.1846 (0.1026)
Accumulated Experience					
γ_1		0.0496 (0.0512)	0.0496 (0.0362)	0.0496 (0.0477)	0.0496 (1.4806)
γ_2		-0.0030 (0.0027)	-0.0030 (0.0019)	-0.0030 (0.0025)	-0.0030 (0.0319)
γ_3		0.0001 (0.0001)	0.0001* (0.0001)	0.0001 (0.0001)	0.0001 (0.0007)
Relative Efficiency of E to L					
Non-university	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2114*** (0.1528)	1.2114*** (0.1151)	1.2114*** (0.1702)	1.2114*** (0.1755)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8118** (0.2555)	0.8118*** (0.1952)	0.8118*** (0.2175)	0.8118 (0.6700)
University	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1847*** (0.2811)	1.1847*** (0.1943)	1.1847*** (0.2661)	1.1847*** (0.3447)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0376** (0.4002)	1.0376*** (0.3123)	1.0376** (0.4025)	1.0376* (0.4607)
Variance estimator					
Person clustering		✓		✓	
Wave clustering				✓	
Bootstrap resampling					✓
Sample Size		108,702	108,702	108,702	108,702
Weighted R^2		0.2708	0.2708	0.2708	0.2708

Second stage robustness check: Additional year-specific controls

Coefficients		(1) Benchmark	(2) + wave $\times$ remoteness	(3) + wave $\times$ dependent children	(4) + both blocks
Labour					
Non-university	$\lambda_{L,1}$	0.0070 (0.0046)	0.0070 (0.0047)	0.0080 (0.0044)	0.0079 (0.0044)
	$\lambda_{L,2}$	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
University	$\lambda_{L,0}$	0.1884*** (0.0321)	0.1877*** (0.0323)	0.2016*** (0.0328)	0.2005*** (0.0329)
	$\lambda_{L,1}$	0.0206*** (0.0050)	0.0207*** (0.0050)	0.0204*** (0.0048)	0.0205*** (0.0048)
	$\lambda_{L,2}$	-0.0002* (0.0001)	-0.0002* (0.0001)	-0.0002 (0.0001)	-0.0002 (0.0001)
Experience					
Non-university	$\lambda_{E,1}$	-0.0474* (0.0223)	-0.0473* (0.0223)	-0.0494* (0.0212)	-0.0495* (0.0213)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0010* (0.0004)	-0.0010* (0.0004)	-0.0010* (0.0004)
University	$\lambda_{E,0}$	-0.6294*** (0.2145)	-0.6186** (0.2132)	-0.6131** (0.2117)	-0.6002** (0.2105)
	$\lambda_{E,1}$	0.0288 (0.0262)	0.0277 (0.0262)	0.0263 (0.0258)	0.0246 (0.0259)
	$\lambda_{E,2}$	-0.0025*** (0.0006)	-0.0024*** (0.0006)	-0.0025*** (0.0006)	-0.0025*** (0.0006)
Inverse Mills Ratio		0.0674 (0.0544)	0.0683 (0.0545)	0.0583 (0.0529)	0.0592 (0.0530)
Disability					
Non-university	$\ln \phi_L(MD, LE)$	-0.1419*** (0.0447)	-0.1423** (0.0448)	-0.1406** (0.0444)	-0.1411** (0.0445)
	$\ln \phi_L(SD, LE)$	-0.1763* (0.0724)	-0.1768* (0.0725)	-0.1642* (0.0705)	-0.1647* (0.0707)
University	$\ln \phi_L(MD, HE)$	-0.1127 (0.0586)	-0.1134 (0.0591)	-0.1094 (0.0578)	-0.1103 (0.0583)
	$\ln \phi_L(SD, HE)$	-0.1846* (0.0893)	-0.1855* (0.0899)	-0.1791* (0.0875)	-0.1798* (0.0882)
Accumulated Experience					
γ_1		0.0496 (0.0512)	0.0491 (0.0509)	0.0508 (0.0509)	0.0510 (0.0509)
γ_2		-0.0030 (0.0027)	-0.0029 (0.0027)	-0.0035 (0.0029)	-0.0034 (0.0029)
γ_3		0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Relative Efficiency of E to L					
Non-university	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2114*** (0.1528)	1.2106*** (0.1526)	1.2228*** (0.1543)	1.2226*** (0.1542)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8118** (0.2555)	0.8102** (0.2551)	0.7869** (0.2534)	0.7851** (0.2531)
University	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1847*** (0.2811)	1.1864*** (0.2823)	1.1875*** (0.2818)	1.1908*** (0.2839)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0376** (0.4002)	1.0379** (0.4014)	1.0502** (0.4031)	1.0498** (0.4053)
Year-specific Control Variables					
Gender		✓	✓	✓	✓
Marital Status		✓	✓	✓	✓
Years of Schooling		✓	✓	✓	✓
A/TS Islander status		✓		✓	✓
Remoteness			✓		✓
Family Structure: Dependent Children				✓	✓
Sample Size		108,702	108,677	108,702	108,677
Weighted R^2		0.2708	0.2711	0.2716	0.2720

Life-cycle profiles of efficiencies: University cohort

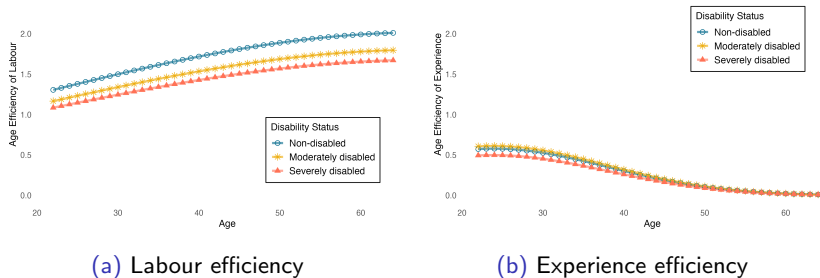


Figure: Life-cycle patterns of labour [λ_L] and experience [λ_E] efficiencies

Life-cycle profiles of effective experience: University cohort

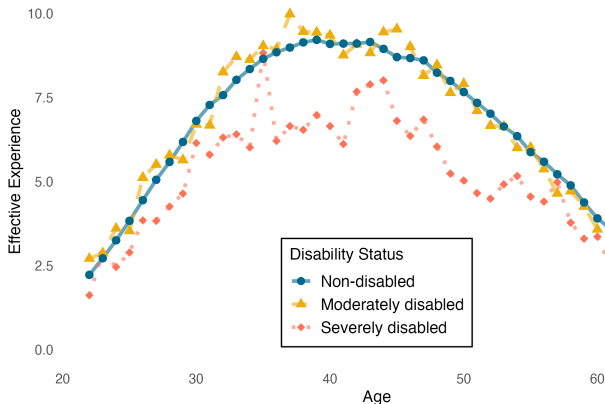
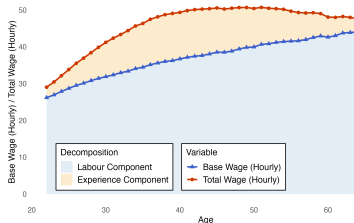
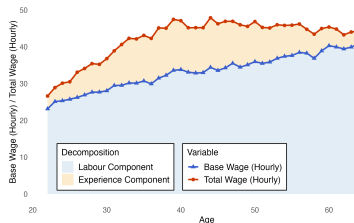


Figure: Life-cycle patterns of effective experience $[\lambda_E \times g(e)]$

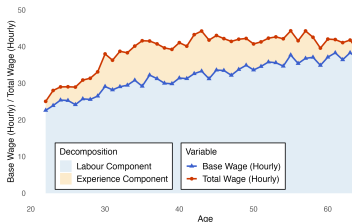
life-cycle profiles of predicted productivity : University cohort



(a) Non-disabled

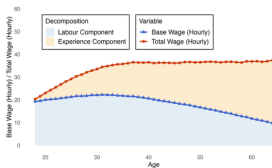


(b) Moderately disabled

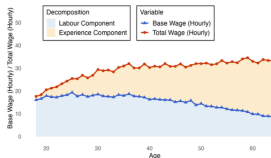


(c) Severely disabled

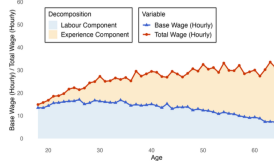
Wage decomposition: Male



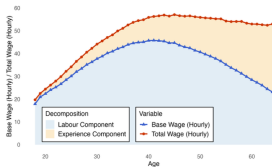
(a) Non-university, Non-disabled



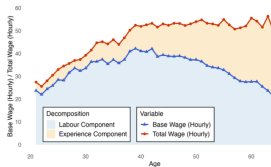
(b) Non-university, Moderately Disabled



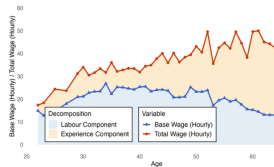
(c) Non-university, Severely Disabled



(d) University, Non-disabled



(e) University, Moderately Disabled

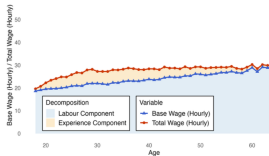


(f) University, Severely Disabled

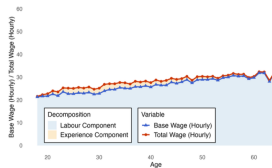
Wage decomposition: Female



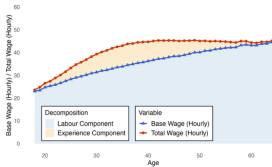
(a) Non-university, Non-disabled



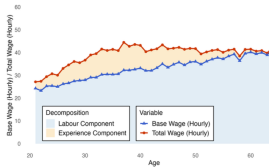
(b) Non-university, Moderately Disabled



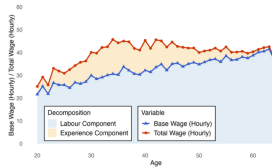
(c) Non-university, Severely Disabled



(d) University, Non-disabled



(e) University, Moderately Disabled



(f) University, Severely Disabled

Taxes and transfers

- ▶ Consumption tax: τ_c
- ▶ Progressive income tax (Tran & Zakariyya, 2022):

$$\text{tax}(y_j) = \max\{0, y_j - \lambda y_j^{1-\tau_y}\}$$

- ▶ Disability support pension (meet hours and medical tests) before age 65, age pension since age 65 (Kudrna, Tran, & Woodland, 2022):

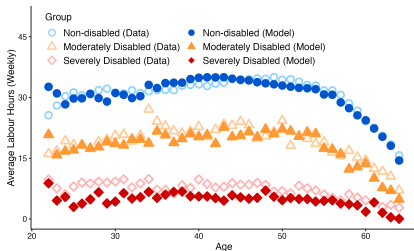
$$\text{pension} = \begin{cases} p^{\max} & \text{if } y^m \leq \bar{y}_1 \\ p^{\max} - \omega^y(y^m - \bar{y}_1) & \text{if } \bar{y}_1 < y^m < \bar{y}_2 \\ 0 & \text{if } y^m \geq \bar{y}_2 \end{cases} \quad (14)$$

Experiment results: Removal of DSP

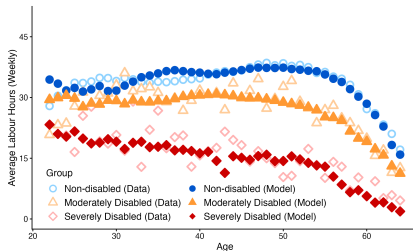
	(1) Benchmark (\$)			(2) Remove DSP (%Δ)		
	<i>Labour Income</i>	<i>Net Income</i>	<i>Consumption</i>	<i>Labour Income</i>	<i>Net Income</i>	<i>Consumption</i>
Non-university						
Non-disabled	1,278,868	973,951	812,231	0%	0%	0%
Moderately Disabled	677,696	563,700	479,769	0%	0%	0%
Severely Disabled	183,846	222,328	192,822	+51.02%	+25.50%	+24.02%
University						
Non-disabled	1,972,446	1,402,538	1,146,349	0%	0%	0%
Moderately Disabled	1,476,734	1,096,580	904,148	0%	0%	0%
Severely Disabled	806,684	653,775	541,823	+9.04%	+7.65%	+6.91%

Figure: Removal of DSP:
Lifetime labour income, net income and consumption

Estimation target: Average labour hours (weekly)



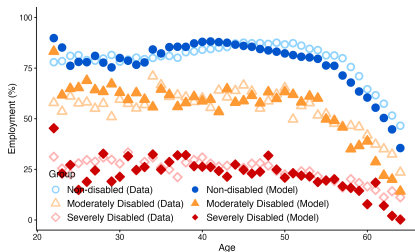
(a) Non-university



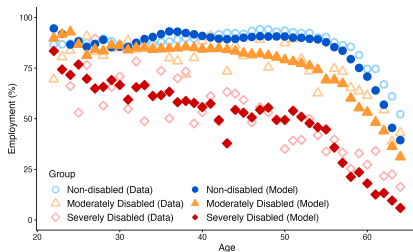
(b) University

Figure: Data VS model: Life-cycle profiles of weekly hours worked by education and disability status

Estimation target: Employment rate



(a) Non-university



(b) University

Figure: Data VS model: Life-cycle profiles of employment rate by education and disability status

Estimation target: DSP recipient ratio

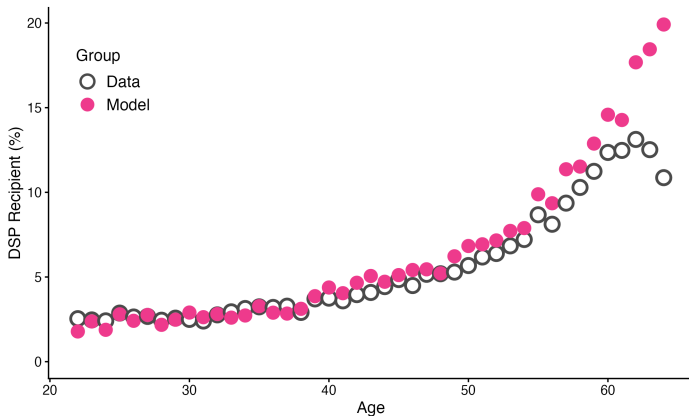
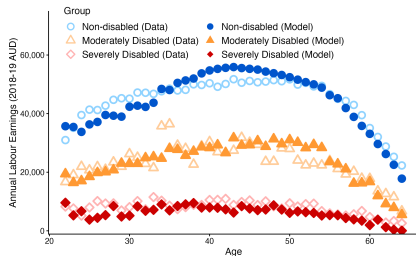
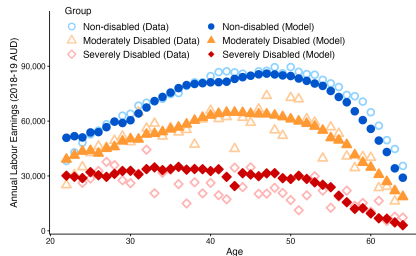


Figure: Data VS model: Life-cycle profiles of DSP participation rate

Model fit: Annual labour earnings



(a) Non-university



(b) University

Figure: Data VS model: Life-cycle profiles of annual labour earnings by education and disability status

Benchmark and counterfactual aggregates

	Benchmark	Experiment 1	Experiment 2
Real Output Per Capita (AUD)	56,902	39,555	57,030
Annual Net Saving Per Capita (AUD)	2,276.5	1,702.9	2,281.0
Labour (Weekly Hours)	23.60	19.13	23.67
Real Consumption Per Capita (AUD)	23,470	17,205	23,511
Mean Accumulated Experience (FTE Years)	14.94	12.13	14.99
Welfare (Model Utility)			
Overall	-231.35	-263.07	-232.05
Non-university, Non-disabled	-229.36	-263.83	-229.36
Non-university, Moderately disabled	-336.06	-376.99	-336.06
Non-university, Severely disabled	-496.26	-516.51	-518.04
University, Non-disabled	-169.69	-190.71	-169.69
University, Moderately Disabled	-212.32	-239.72	-212.32
University, Severely Disabled	-293.37	-317.62	-291.71

Robustness: model without learning by doing

- ▶ Alternative model in which experience is **not endogenous**: the learning-by-doing channel is switched off, and each group is endowed with its estimated *total* wage profile (labour and experience components together, taken as given).
- ▶ The model is recalibrated to the same targets, and both experiments are repeated.
- ▶ The following slides compare the benchmark (learning by doing) with the no-learning model: the benchmark fits the targets more closely, and the experience experiment is larger because removing experience also removes the incentive to accumulate it.
- ▶ Aggregate and distributional conclusions are unchanged.

Calibration fit: benchmark versus no learning

Group	Hours RMSE, Benchmark	Hours RMSE, No Learning	Employment RMSE (pp), Benchmark	Employment RMSE (pp), No Learning	Earnings RMSE (%), Benchmark	Earnings RMSE (%), No Learning
Non-university, no disability	1.53	1.90	3.41	5.19	7.9	14.4
Non-university, moderate disability	2.50	3.25	8.05	9.22	17.5	20.8
Non-university, severe disability	2.89	2.67	6.35	7.89	32.0	31.2
University, no disability	1.69	1.62	3.27	3.43	5.1	10.2
University, moderate disability	2.90	3.40	5.69	6.13	15.3	23.2
University, severe disability	3.87	4.47	10.80	12.02	37.8	40.2
DSP participation	- - -	- - -	1.97	1.97	- - -	- - -

Figure: Root-mean-squared calibration errors by group

Removal of the experience component: benchmark versus no learning

Group	Labour Income (%), Benchmark	Labour Income (%), No Learning	Net Income (%), Benchmark	Net Income (%), No Learning	Consumption (%), Benchmark	Consumption (%), No Learning
Non-university, no disability	-32.25	-28.03	-28.38	-23.56	-28.55	-21.67
Non-university, moderate disability	-33.57	-32.03	-28.24	-25.96	-27.99	-24.22
Non-university, severe disability	-24.51	-29.86	-14.77	-18.41	-14.76	-17.89
University, no disability	-24.80	-21.94	-21.86	-18.50	-22.58	-17.23
University, moderate disability	-29.18	-24.26	-25.79	-20.45	-26.10	-18.84
University, severe disability	-26.45	-23.71	-22.16	-19.14	-22.02	-17.74

Figure: Changes in lifetime variables (%)

Removal of the DSP: benchmark versus no learning

Group	Labour Income (%), Benchmark	Labour Income (%), No Learning	Net Income (%), Benchmark	Net Income (%), No Learning	Consumption (%), Benchmark	Consumption (%), No Learning
Non-university, no disability	0.00	0.00	0.00	0.00	0.00	0.00
Non-university, moderate disability	0.00	0.00	0.00	0.00	0.00	0.00
Non-university, severe disability	+51.02	+35.78	+25.50	+17.58	+24.02	+15.69
University, no disability	0.00	0.00	0.00	0.00	0.00	0.00
University, moderate disability	0.00	0.00	0.00	0.00	0.00	0.00
University, severe disability	+9.04	+7.34	+7.65	+6.19	+6.91	+5.13

Figure: Changes in lifetime variables (%)

Aggregate outcomes: benchmark versus no learning

	Benchmark: Baseline	Benchmark: Remove Experience	Benchmark: Remove DSP	No Learning: Baseline	No Learning: Remove Experience	No Learning: Remove DSP
Real Output Per Capita (AUD)	56,902	39,555	57,030	62,828	46,286	62,938
Annual Net Saving Per Capita (AUD)	2,276.5	1,702.9	2,281.0	3,146.8	1,998.8	3,152.4
Labour (Weekly Hours)	23.60	19.13	23.67	23.48	23.05	23.53
Real Consumption Per Capita (AUD)	23,470	17,205	23,511	25,716	20,479	25,748
Mean Accumulated Experience (FTE Years)	14.94	12.13	14.99	- - -	- - -	- - -
Welfare (Model Utility), Overall	-231.35	-263.07	-232.05	-188.89	-224.07	-189.48

Figure: Baseline and counterfactual aggregates