

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

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Abstract

This paper examines how disability affects labour productivity and lifetime earnings. We distinguish its effects on current labour productivity from its effects on the accumulation of work experience that drives earnings growth. Using Australian panel data, we estimate a two-stage Heckman selection model that allows for selection into employment and recovers labour and experience efficiency profiles by disability status and education. Moderate and severe disability reduce labour efficiency by 12% and 17%, respectively. Their effects on experience efficiency differ sharply: moderate disability raises it by 6%, while severe disability lowers it by 23%, and by 32% among workers without a university degree. Because returns to experience increase with age, these differences compound over the life cycle. Severely disabled workers earn 61–84% less lifetime labour income than comparable non-disabled workers, with the largest losses among non-university workers. We embed the estimated productivity profiles in a structural life-cycle model of Australia’s disability income support system. Counterfactual simulations show that removing the experience component of productivity reduces lifetime earnings by 23–33%, by more for non-university workers than for university workers in every disability state, highlighting the importance of accumulated work experience for lifetime earnings. Eliminating the Disability Support Pension increases lifetime earnings for severely disabled workers by 7% among university graduates and 37% among non-university workers, concentrating the response in the group with the largest lifetime loss. The results show that disability affects earnings through two distinct human capital channels with different life-cycle dynamics. Ignoring this distinction understates both the magnitude and the distribution of disability’s lifetime economic costs.

JEL Classification: H53, I38, J22, J24, J31

Keywords: Disability; Human Capital; Work Experience; Earnings; Disability Insurance; Life-cycle Model

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1 Introduction

Disability is a growing economic and social challenge across the United States and other OECD countries. In the United States, the share of working-age adults receiving federal Disability Insurance (DI) benefits increased from 2.2% in the late 1970s to 3.6% before the 2007-09 global financial crisis, and reached 4.6% by 2013 (Liebman, 2019). Similar trends are evident elsewhere. The World Health Organization estimates that 1.3 billion people, around 16% of the global population, live with a significant disability (WHO, 2023). In the United Kingdom, one quarter of people were classified as disabled in 2023-24, including 24% of working-age adults and more than 40% of people above state pension age (Department for Work and Pensions, 2025). Across the European Union, 23.9% of people aged 16 and over reported a long-standing activity limitation in 2024, with prevalence ranging from 14.5% in Italy to 41.2% in Latvia (Eurostat, 2025).

Disability can affect earnings through several mutually reinforcing channels. First, it can reduce current employment and hours by limiting work capacity, raising the cost of market work, or making job search and workplace adjustment more difficult. Second, conditional on working, disability can lower labour efficiency by reducing the amount of effective labour supplied per hour. Third, disability can slow the accumulation of work experience when weaker labour force attachment reduces time spent in employment, and it can also change the wage return to a given stock of experience if health limitations affect the tasks, occupations, or career ladders through which experience is rewarded. Finally, disability income support and related transfers alter disposable income and labour supply incentives, partly insuring households against earnings losses while also changing the payoff to work. These channels imply that the earnings cost of disability is dynamic: it reflects not only a contemporaneous wage or employment penalty, but also the cumulative effect of disability on human capital accumulation and labour supply over the life cycle. This paper aims to better understand these channels and their implications for lifetime earnings, social insurance, and aggregate productivity.

Australia provides an ideal setting to study these mechanisms. Disability is both widespread and increasing, while rich longitudinal data and well-defined institutions allow the underlying earnings channels to be identified. In 2022, 5.5 million Australians (21.4% of the population) reported a disability, up from 4.4 million (18%) in 2018, and participation in the National Disability Insurance Scheme (NDIS) continues to grow (ABS, 2024; AIHW, 2025). Population ageing, rising chronic and mental health conditions, and improved diagnosis have all contributed to this increase (AIHW, 2025). Disability prevalence reaches 52.3% among people aged 65 and over, and 7.9% of Australians live with a profound or severe disability (ABS, 2024). Australia's tax-and-transfer system, including the Disability Support Pension (DSP), the Age Pension, and progressive income taxation, also provides a natural setting in which to examine the trade-off between insurance and work incentives. The Household, Income and Labour Dynamics in Australia (HILDA) Survey follows individuals from 2001 to 2024 and records disability status, employment, wages, education, work experience, and household income. These data allow us to separate the effects of disability on current labour productivity from its effects on the accumulation of work experience over the life cycle.

Our analysis proceeds in two parts: an empirical model for wage decomposition and a structural life-cycle model for counterfactual analysis. In the empirical part, we build on Katz and Murphy (1992), Jeong, Kim and Manovskii (2015) and Kim and Rhee (2022) to model workers as supplying two forms of human capital: pure labour and work experience. Using HILDA Survey data from 2001-2024, we estimate a two-stage Heckman selection model to recover age-efficiency profiles for labour and experience by disability status and education. Rather than treating disability as shifting wages through a single reduced-form channel, we show how disability differentially affects heterogeneous human capital components while correcting for non-random

employment selection.

The two-stage model allows for selection into employment, though in our estimates the correction turns out to be small: the inverse Mills ratio is positive, the sign that positive selection would imply, but it is not statistically distinguishable from zero, so we do not claim to detect selection on unobservables. We find that moderate and severe disability reduce labour efficiency by an average of 12.33% and 17.30% respectively, with little difference between education groups. The effects on experience efficiency separate the two severity levels. Moderate disability raises experience efficiency, by 5.50% on average, while severe disability lowers it by 22.55% on average, and the severe penalty is far larger for non-university workers (31.64%) than for university graduates (13.46%). Decomposing total productivity into labour and experience components shows that the labour component accounts for most of productivity at every age, while the experience component follows a hump shape: it rises steeply through the twenties, peaks at around a third of total productivity in the mid to late thirties, and declines thereafter as the fall in experience efficiency outweighs continued accumulation. The experience share is larger for non-university workers than for university workers at almost every age. The empirical estimates therefore show that disability affects both the level and the composition of productivity over the life cycle.

In the structural part, we quantify the lifetime costs of disability within an overlapping generations (OLG) model calibrated to the Australian economy. While U.S. studies develop life-cycle models of disability insurance, and Australian OLG studies analyse taxation, pensions and demographic change, there is limited structural work that embeds disability-related productivity losses and the DSP in one quantitative Australian framework (Kitao, 2014; Low and Pistaferri, 2015; Michaud and Wiczer, 2021; Kim and Rhee, 2022; Kudrna, Tran and Woodland, 2022; Tran and Woodland, 2014). Our benchmark model incorporates disability-specific productivity profiles, the DSP, the Age Pension, and the Australian tax system to study how disability affects labour supply, earnings, and consumption over the life cycle.

In the calibrated benchmark model, we find that disability substantially lowers lifetime labour earnings, net income and consumption relative to the non-disabled. Moderately disabled individuals earn about 46.9% less lifetime labour income than non-disabled workers with the same education among non-university workers, and about 21.1% less among university workers. The penalties for severely disabled individuals are much larger, at about 84.4% and 60.5% respectively. These gaps combine the estimated wage penalties with large differences in employment and hours, and the severe category includes respondents who report being unable to work at all, whose lifetime labour income is close to zero. The gap is larger for non-university workers because their earnings rely more heavily on the accumulated-experience channel that disability damages most. The consumption gap is smaller but still substantial: severely disabled non-university workers consume about 25.3% of the lifetime amount consumed by non-disabled counterparts, and severely disabled university workers about 46.3%. The tax-and-transfer system partially compresses these gaps: reductions in net income are consistently less severe than those in gross labour income, reflecting the redistributive role of the DSP and the progressivity of the Australian tax system.

Two counterfactual experiments are conducted. The first removes the experience component from the productivity process and finds that lifetime labour income falls for all groups, with losses ranging from 22.5% for non-disabled university workers to 32.9% for moderately disabled non-university workers. Every non-university group loses more than every university group, indicating that accumulated work experience is a particularly important component of the lifetime earnings of workers without a degree. The second eliminates the DSP. Because the model restricts DSP medical eligibility to severely disabled individuals, this counterfactual leaves non-disabled and moderately disabled groups unchanged. Among severely disabled

individuals, labour earnings rise by 36.7% for non-university workers and by 6.7% for university workers, as the loss of transfers induces greater labour force participation and hours worked. The much smaller response among university-educated severely disabled individuals reflects their position relative to the means test: most already earn enough to be partly or fully tapered out of the payment, so its removal changes their budget set far less. Because non-university workers combine the largest lifetime income loss with the largest earnings response to DSP removal, the program’s insurance value and its incentive cost are concentrated in the same group rather than offsetting across different populations. These results point to a central policy trade-off: the DSP protects the consumption of severely disabled individuals against income risk, but it also weakens work incentives for eligible workers, and it does so most for the very group whose consumption protection is most valuable; the welfare implications therefore depend on the balance between consumption protection, incentives, and leisure.

Related literature. This paper contributes to three strands of the literature. First, it builds on the heterogeneous human capital and wage determination literature, pioneered by [Katz and Murphy \(1992\)](#) and extended by [Card and Lemieux \(2001\)](#) and [Fox and Smeets \(2011\)](#). [Katz and Murphy \(1992\)](#) model workers as supplying two distinct inputs, pure labour and work experience, within a CES production framework, decomposing changes in the US wage structure into supply and demand factors over 1963-1987. [Card and Lemieux \(2001\)](#) extend this to cohort dynamics, while [Fox and Smeets \(2011\)](#) apply the heterogeneous input approach at the firm level. Our empirical contribution is to bring this framework to the Australian disability context, estimating how disability differentially shifts labour and experience efficiency profiles over the life cycle, rather than treating disability as a single wage-shift parameter.

Second, the paper connects to the literature on disability, labour supply and human capital, including [Jeong, Kim and Manovskii \(2015\)](#), [Keane \(2016\)](#), [Gilleskie and Hoffman \(2014\)](#) and [Kim and Rhee \(2022\)](#). [Jeong, Kim and Manovskii \(2015\)](#) refine the Katz-Murphy measurement approach using PSID panel data, showing that demographic changes in the supply of experience can account for nearly all of the observed movement in the return to experience, with little role for demand shifts. [Keane \(2016\)](#) shows that once wages are allowed to depend endogenously on accumulated work experience, labour supply elasticities can no longer be recovered independently of the wage process and become substantially larger than under the standard exogenous-wage life-cycle model. [Gilleskie and Hoffman \(2014\)](#) show that disability reduces wages both directly through reductions in health capital and indirectly by raising the likelihood of occupational and employer transitions that erode tenure-based human capital. Most closely related, [Kim and Rhee \(2022\)](#) estimate the same labour-experience decomposition for the United States and embed it in a general equilibrium life-cycle model in which disability status evolves stochastically over the life cycle; removing the DI program shifts the equilibrium relative price of experience, and they show that labour-experience complementarity determines whether this raises or lowers aggregate productivity. Our analysis differs in three respects. First, we model disability as a permanent type fixed at labour-market entry rather than a stochastic Markov process, which lets us calibrate directly to the joint life-cycle distribution of disability and education observed in HILDA, but means our counterfactuals speak to the redistributive and incentive effects of the DSP among the already disabled rather than to the ex-ante insurance value of the program. Second, our counterfactuals hold factor prices fixed, isolating the direct productivity and income channels rather than the general-equilibrium price responses that drive the aggregate results in [Kim and Rhee \(2022\)](#). Third, we embed the estimated profiles in the Australian institutional setting: the DSP, the Age Pension and a progressive income tax, rather than the US DI-and-Medicare system, allowing us to quantify the redistributive role of Australia’s tax-and-transfer system directly.

Third, the structural part contributes to the life-cycle and OLG literature on disability insurance, which builds on structural life-cycle labour supply models with health more broadly, such as [French \(2005\)](#), who models health as a stochastic shock shaping retirement timing under borrowing constraints. We instead treat disability as a permanent type fixed at labour-market entry that shifts the composition, rather than the timing, of lifetime productivity. This strand includes [Kitao \(2014\)](#), [Low and Pistaferri \(2015\)](#), [Michaud and Wiczer \(2021\)](#) and [Jung and Tran \(2022\)](#). [Kitao \(2014\)](#) develops a life-cycle model of unemployment and disability insurance, finding that the health insurance component is critical to program take-up. [Low and Pistaferri \(2015\)](#) estimate the insurance-incentive trade-off in the US disability program, showing that reforms that improve targeting raise welfare despite work disincentives. [Michaud and Wiczer \(2021\)](#) show that falling wages at the bottom of the earnings distribution drove much of the rise in the social security disability insurance (SSDI) take-up during the 1980s and 1990s, explaining approximately two-thirds of the male employment decline over that period. These papers study disability insurance primarily through application decisions, screening errors, health transitions, return-to-work incentives and welfare. Our contribution is different. We focus on productivity mechanisms and lifetime distributional consequences.

Previous Australian research shows that disability and poor health substantially affect labour market outcomes. Using early waves of the HILDA Survey, [Wilkins \(2004\)](#) finds that disability significantly reduces labour force participation, particularly among older workers. [Cai \(2009\)](#) and [Cai \(2021\)](#) estimate the wage effects of health conditions using Heckman selection models and documents persistent earnings penalties that increase with disability severity. While this literature establishes sizeable participation and wage penalties, it does not identify the underlying mechanisms. In particular, it does not distinguish whether disability reduces earnings through lower current labour productivity, weaker returns to accumulated work experience, or differences in life-cycle labour supply. Nor does it quantify how these productivity losses translate into lifetime earnings and welfare within Australia’s tax-and-transfer system. Broader Australian studies, such as [Cai and Jeffrey Waddoups \(2012\)](#), examine heterogeneity in human capital, but they do not model disability-specific human capital accumulation or integrate the estimates into a structural life-cycle framework. Our paper fills this gap by combining an empirical decomposition of disability-related productivity with a structural life-cycle model calibrated to Australian institutions.

More recently, [Deshpande, Kaplan and Leigh-Wood \(2025\)](#) exploit a regression discontinuity around a 2014 DSP medical-review reform to estimate the effect of DSP removal on household income and health care use, finding a zero average income effect that masks sharp heterogeneity by family structure: recipients living with family are fully insured by higher parental and spousal earnings, while those living alone suffer an income loss and a sharp rise in antipsychotic use. Their reduced-form earnings response is directionally consistent with our structural counterfactual, in which removing the DSP raises lifetime labour earnings of severely disabled workers by 36.7% (non-university) and 6.7% (university). Our framework, however, abstracts from the family-insurance and mental health margins that their quasi-experimental design captures.

The remainder of this paper is organised as follows. Section 2 provides an overview of data and empirical facts from Australia. Section 3 presents the empirical analysis, with detailed descriptions of the data, methodology, identification strategy, and estimation results. Section 4 outlines the structural analysis, including the model framework, individual optimisation problem, calibration procedure, and quantitative findings. Finally, Section 5 summarises the main empirical and structural results.

2 Empirical facts

This section documents key empirical facts about disability in Australia using the HILDA Survey, beginning with the rising prevalence of long-term health conditions and disability shown in Figure 1.

Figure 1: **Longitudinal Prevalence of Long-term Health Condition, Impairment or Disability**



Notes: This figure plots the share of the working-age population, ages 15 to 64, reporting any long-term health condition, impairment or disability. It is based on the HILDA Survey question: "Do you have any long-term health condition, impairment, or disability that restricts you in your everyday activities, and has lasted or is likely to last, for 6 months or more?". The series is deliberately broader than the three-way classification used in the rest of the paper: it counts everyone who reports a condition, including those who report no resulting work limitation.¹ A detailed description of the criteria used to define disability status is provided in Appendix A.1.

Data. This paper uses data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is a nationally representative, household-based longitudinal survey funded by the Australian Government Department of Social Services and managed by the Melbourne Institute. The survey collects detailed information on economic wellbeing, household and family formation, labour market dynamics, income, health, education, and other individual and household characteristics. We use General Release 24, which contains 24 annual waves of data collected between 2001 and 2024. Income variables generally refer to the preceding financial year, so the income information spans financial years 2000-01 to 2023-24.

The HILDA Survey began in 2001 with a sample of Australian households living in private dwellings. All household members aged 15 years and over were eligible for interview. The survey follows individuals over time, with original sample members and their household members forming the basis of the longitudinal panel. Children born to, or adopted by, continuing sample members are added to the panel, and new entrants to households are also interviewed while they remain living with a continuing sample member. This design allows HILDA to track individuals and households over the life course while maintaining information on changing household composition.

The number of respondents varies across waves. In General Release 24, 13,969 persons were interviewed in wave 1, 17,612 in wave 11, and 17,178 in wave 24. The wave-to-wave response rate is relatively stable over the panel, ranging from 86.9 percent to 97 percent. HILDA collects information through several survey instruments, including household-level and person-level questionnaires.¹ In wave 1, the main instruments

¹A detailed description of the HILDA data files and survey instruments is provided in the HILDA User Manual (Summerfield et al., 2025).

included the Household Form, Household Questionnaire, Person Questionnaire, and Self-Completion Questionnaire. From wave 2 onward, the person questionnaire distinguishes between continuing respondents and new respondents.

Our empirical analysis primarily uses individual-level information from the responding person files, supplemented where necessary by household-level and enumerated person information. The key variables include age, disability status, education, work history, labour force status, hours worked, wages, income, household characteristics, and time-use measures. Details on sample construction, variable definitions, and sample restrictions are provided in Appendix A.1. Summary statistics by age, disability status, and education level, together with descriptive evidence on cumulative work experience, are reported in Appendix A.3.

Disability trends in Australia. The World Health Organization’s International Classification of Functioning, Disability and Health defines disability broadly to include impairments in body function or structure, limitations in undertaking activities, and restrictions on social and economic participation. Disability is shaped by the interaction between an individual’s health conditions and personal and environmental circumstances, and therefore varies considerably in type and severity.

In Australia, the prevalence of long-term health condition or disability has increased over recent decades, as shown in Figure 1, showing health as an increasingly important economic and social policy issue. Health-related limitations can create persistent barriers to education, employment, and career progression, reducing labour force participation, earnings, and productivity. These effects can accumulate over the life cycle: disrupted education and weaker attachment to the labour market limit the acquisition of skills and work experience, contributing to lower income and wealth among people with disabilities. The rising prevalence therefore has implications not only for individual wellbeing, but also for aggregate human-capital accumulation, workforce capacity, inequality, and demand for public support.

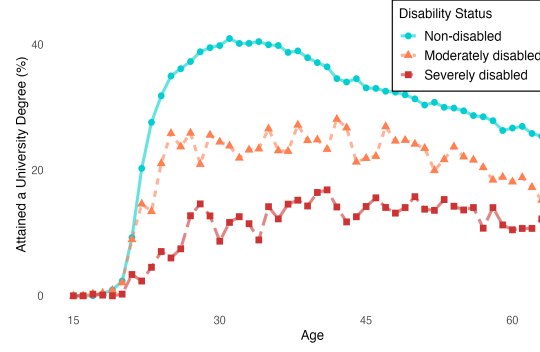
Education and employment. Disability is associated with disadvantage in both human capital accumulation and labour market participation. Individuals with disabilities are less likely to attain post-school qualifications, limiting their skills and productivity.

Figure 2 depicts the proportion of individuals with at least a university-level degree by disability status. Educational attainment is substantially lower among individuals with moderate and severe disabilities than among their non-disabled counterparts. Averaged over ages 18 to 64, 31% of non-disabled individuals hold a university qualification, against 21% of the moderately disabled and 12% of the severely disabled; over the ages at which attainment has settled, 35 to 64, the three figures are 33%, 22% and 13%.

These educational disparities translate into weaker employment outcomes. Figure 3 illustrates disparities in employment status (left panel) and full-time employment status among employed individuals (right panel), according to disability status. Through the prime working ages, 30 to 54, employment averages 86% for the non-disabled, 65% for the moderately disabled and 30% for the severely disabled; across the full working-age range the three rates are 79%, 57% and 25%. Among those who are employed, disability is also associated with less full-time work. The full-time share is 70% for the non-disabled, 59% for the moderately disabled and 44% for the severely disabled, so more than half of employed individuals with a severe disability work part-time.

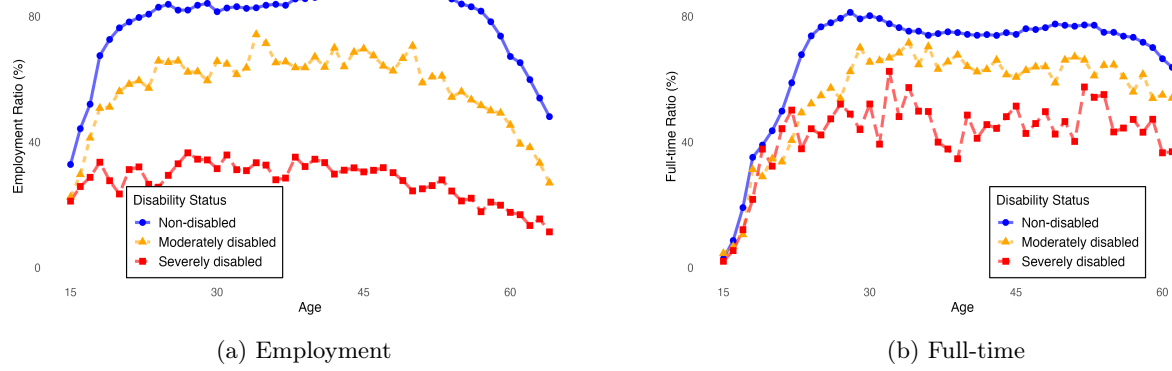
Income sources over the life cycle. Lower educational attainment, reduced labour force participation, and fewer hours worked combine to generate persistently lower labour income, increasing reliance on public income support throughout the working life. Figure 4 presents life-cycle income profiles, disaggregated into

Figure 2: University Education by Disability Status



Notes: This figure illustrates life-cycle patterns of university-level educational attainment by disability status. The definition of university education is detailed in Appendix A.1.

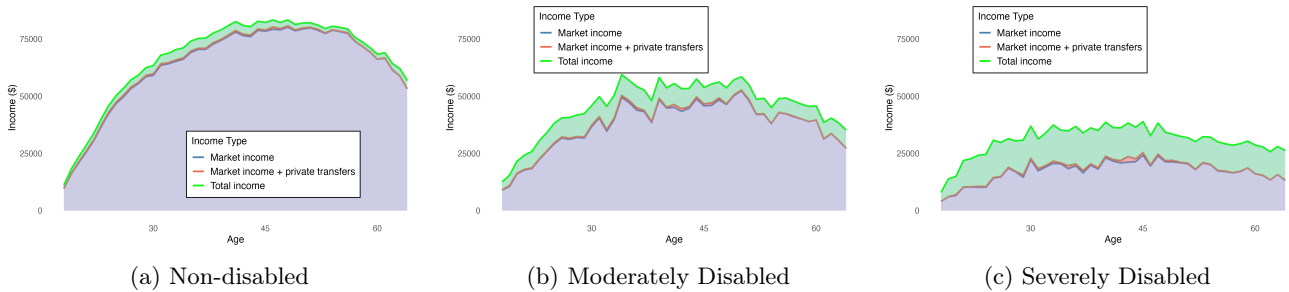
Figure 3: Life-cycle Employment and Full-time Ratios



Notes: This figure presents life-cycle patterns of employment and full-time status by disability status. The latter is computed exclusively among employed individuals. Employment refers to individuals who are actively engaged in paid work, while non-employment encompasses those who are either unemployed or not participating in the labour force.

market income, private transfers, and public transfers, by disability status. Individuals with moderate or severe disabilities have substantially lower incomes than those without disabilities, and the gap is much wider in market income than in total income. Averaged over ages 18 to 64, market income for the severely disabled is 28% of the non-disabled level and for the moderately disabled 61%, while total income including transfers is 47% and 70% respectively. The difference between the two comparisons is the tax-and-transfer system: public transfers account for 41% of total income among working-age individuals with severe disabilities and 16% among the moderately disabled, against 4% among the non-disabled. In contrast, individuals without disabilities derive the majority of their income from market-based sources.

Figure 4: **Income Sources by Disability Status**



Notes: These panels show life-cycle income composition by disability status, with the blue, red, and green shaded areas indicating market income, private transfers, and public transfers, respectively. Market income is a combination of wages and salaries, business and investment incomes, and regular private pensions. All income figures have been adjusted for inflation using the Consumer Price Index (CPI) and are reported in 2018-2019 prices. Further details on the CPI adjustment procedure are provided in Appendix A.2.

These patterns are not specific to the HILDA panel. In national disability statistics, only 17% of people with disability aged 20 and over, and 11% of those with severe or profound disability, hold a bachelor's degree or higher, compared with 35% of people without disability; fewer than one in two working-age people with disability are employed, and 54% of those employed work part-time (ABS, 2018; AIHW, 2022).

Together, these descriptive findings underscore the multifaceted disadvantages faced by individuals with disabilities, reflected in weak labour market attachment and poor educational outcomes. Such patterns suggest the presence of barriers to skill accumulation and productivity growth, motivating an empirical investigation of how disability affects individuals' economic trajectories over the life cycle. To disentangle the mechanisms through which disability status shapes labour market outcomes, we adopt the framework of Kim and Rhee (2022), who extend Jeong, Kim and Manovskii (2015) by incorporating disability-related heterogeneity in individual productivity, and apply the model to Australian data.

3 Estimation

3.1 Wage equation

In the production process, workers are presumed to contribute two distinctive inputs: (pure) labour and experience. The former represents physical effort, while the latter constitutes human capital accumulated from participating in the labour market. As described in Jeong, Kim and Manovskii (2015) and Kim and

Rhee (2022), these concepts correspond to "pure labour" and "work experience" in the seminal paper of Katz and Murphy (1992).

A worker i 's hourly wage rate w , used as a proxy for labour productivity, can be decomposed as $w_i = R_L \hat{l}_i + R_E \hat{e}_i$, where $\hat{l}_i$ denotes endowed labour efficiency units, $\hat{e}_i$ denotes endowed experience efficiency units, and R_L and R_E are the corresponding prices of these efficiency units.

In this framework, labour efficiency captures the part of the wage offer associated with current effective labour input, conditional on age, disability status, education, and other controls. Experience efficiency captures how the wage return to accumulated employment history varies over the life cycle and across disability and education groups. These objects should therefore be read as wage-based efficiency indices, not direct measures of biological health, task productivity, or employer assessments of ability.

To incorporate the effects of disability into the wage equation, we follow the extended modeling approach in Kim and Rhee (2022). Disability affects endowed human capital, with its impact varying in severity across different ages. Hence, the endowed labour efficiency units $\hat{l}_i$ for worker i of age j and disability status dis is denoted as $\lambda_L(j, dis_i)$. The endowed experience efficiency units $\hat{e}_i$ consist of two components, namely a deterministic life-cycle profile of experience $\lambda_E(j, dis_i)$ that varies by age j and disability status dis , and an endogenously cumulative work experience function that varies by employment history e . This is because workers within the same age cohort or disability status may have different employment histories e at each given point in time t . To account for this variability, a function of accumulated experience with non-linear effects $g(e)$ is introduced, with $g(e) = e_{it} + \gamma_1 e_{it}^2 + \gamma_2 e_{it}^3 + \gamma_3 e_{it}^4$. Therefore, the endowed experience efficiency units $\hat{e}_i$ of a worker of age j , with disability status dis_{it} and reported employment history e , is denoted as $\lambda_E(j, dis_{it}) \cdot g(e)$. The hourly wage equation can be rewritten as

$$w_{it}(j, dis, e) = R_L \cdot \lambda_L(j, dis_{it}) + R_E \cdot \lambda_E(j, dis_{it}) \cdot g(e). \quad (1)$$

Disability status is categorised into three groups, denoted as $dis_{it} \in \{ND, MD, SD\}$, where ND , MD and SD represent workers who are non-disabled, moderately disabled, and severely disabled, respectively. Wages in the model are also allowed to vary by education level, represented as $edu_{it} \in \{LE, HE\}$. Here, LE refers to individuals with qualifications up to an advanced diploma or below, while HE refers to individuals who have attained university-level qualifications, such as a bachelor's degree, or higher. Detailed explanations of how these classifications are constructed or defined with HILDA data are provided in Appendix A.1.

Building on Equation 1, we incorporate education and prepare for the log-wage transformation by rewriting it as

$$w_{it}(j, dis, e, edu) = R_L \cdot \lambda_L(j, dis_{it}, edu_{it}) \cdot \left[1 + \Pi_E \cdot \frac{\lambda_E(j, dis_{it}, edu_{it})}{\lambda_L(j, dis_{it}, edu_{it})} \cdot g(e) \right], \quad (2)$$

where $\Pi_E \equiv R_E/R_L$ defines the relative price of experience to labour. The life-cycle profiles of labour and experience efficiency units are measured using a polynomial function of age, expressed as $\tilde{\lambda}_X(j) = \exp(\lambda_{X,0} + \lambda_{X,1}j_{it} + \lambda_{X,2}j_{it}^2)$, and a scaling factor, $\phi_X(dis_{it}, edu_{it})$, that captures the effects of disability by educational attainment, so that $\lambda_X(j, dis_{it}, edu_{it}) = \phi_X(dis_{it}, edu_{it}) \cdot \tilde{\lambda}_X(j)$, where $X = L$ (Labour) or E (Experience). Thus, the log-wage transformation of Equation 2 is given by

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

where d_t are wave (year) dummies replacing $\ln(R_{L_t})$, $\lambda_{E/L} \equiv \lambda_E - \lambda_L$ signifies the relative efficiency of experience to labour, X_{it} accounts for individual characteristics and ϵ_{it} represents the error term. Individual characteristics encompass interaction terms between state and wave, and year-specific demographic factors including gender, years of schooling and marital status. By normalising $\lambda_{L,0}(LE)$, $\lambda_{E,0}(LE)$, $\phi_L(edu_{it}, ND)$ and $\phi_E(edu_{it}, ND)$ to one, the coefficients $\phi_L(edu_{it}, MD)$ and $\phi_E(edu_{it}, MD)$ estimate the relative efficiencies of labour and experience for moderately disabled individuals compared to non-disabled individuals within the same educational cohort. This explanation similarly applies to severely disabled workers.

3.2 Identification strategy

Wages are observed only for employed workers. This limitation is particularly relevant for non-employed moderately or severely disabled individuals, as the observed wages of those who are employed may differ substantially from their unobserved wage distribution, leading to selection bias. To address this issue, we employ a two-stage estimation procedure as proposed by Heckman (1979). In the first stage, we estimate a probit regression for the employment decision, incorporating an instrumental variable to satisfy the exclusion restriction. This is given by

$$\text{Probability}(emp_{it} = 1 | X_{it}, Z_{it}) = \Lambda(X_{it}, Z_{it}), \tag{4}$$

where emp is employment status, Λ is the probit function, X is a vector of explanatory variables and Z is an instrument. The inverse Mills ratio derived from this first-stage regression is then included in Equation 3 to correct for the potential bias arising from non-random sample selection. The first-stage explanatory variables include financial-year dummies, demographic factors, and socioeconomic characteristics.

Identification in the Heckman selection model relies on the validity of an exclusion restriction: a variable that influences employment selection but is uncorrelated with the error term in the outcome equation. Instrument relevance is testable and is tested formally: a Wald test of the null that the instrument has no explanatory power in the employment probit, alongside the partial F statistic from the corresponding linear probability model. The exclusion restriction is not directly testable, but a diagnostic is available. We add the instrument to the second-stage wage equation and test its significance with a Wald test, the null being that it has no direct effect on wages once employment and the included covariates are conditioned on. Failure to reject is consistent with the exclusion restriction, though it does not prove validity.

While Low and Pistaferri (2015) and Kim and Rhee (2022) simulate taxes and transfers for a representative earner by state and year to construct instrumental variables, we instead employ the one-year lagged weekly time spent on household errands as the sole exclusion restriction. The identifying assumption is that lagged errands affect current employment by changing the opportunity cost of market work, but do not directly

Table 1: **First-stage Probit Regression Results**

Variable	Coefficient	Effect on the Probability of Employment	
		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

Notes: The first-stage regression controls for individual characteristics and wave dummies, with individual sample weights incorporated. The full regression table is provided in Appendix A.4. Clustered standard errors are stated in parentheses. Significance levels are denoted as follows: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

affect hourly wages conditional on employment and observed controls. This assumption is plausible for three reasons. First, the variable is lagged, making it less likely to reflect contemporaneous wage shocks or current job conditions. Second, household errands primarily capture a non-market time-allocation constraint that should matter for whether an individual can participate in paid work, rather than for the wage rate received once employed. Third, the wage equation controls for disability status, education, age, gender, marital status, financial-year effects, and state-by-year conditions, which capture many observed determinants of productivity and wage offers. Nevertheless, the exclusion restriction cannot be tested directly. Lagged errands may still proxy for persistent household responsibilities, unobserved health, preferences for home production, or job flexibility that could also be related to wages. We therefore interpret the Heckman correction as addressing employment-selection bias under a plausible but maintained exclusion restriction. A detailed justification for this choice, including concerns with contemporaneous measures and supporting empirical evidence, is provided in Appendix A.4.

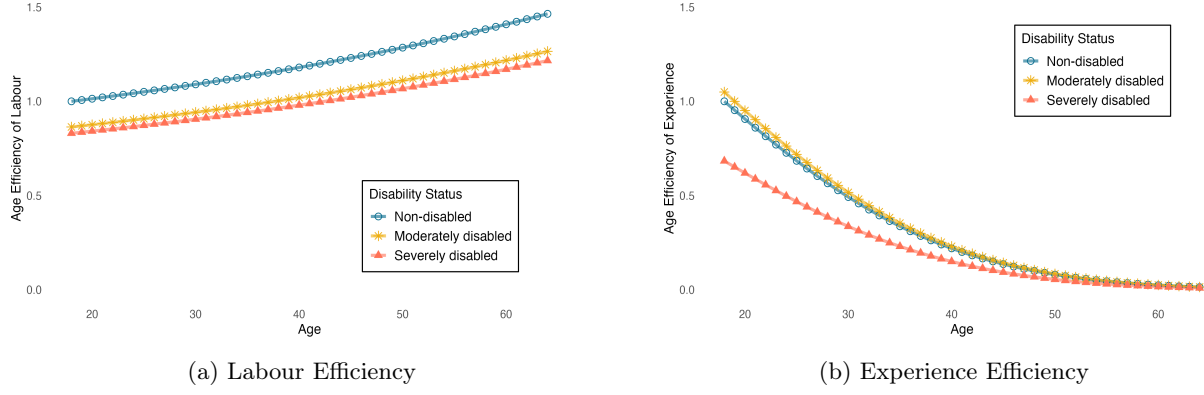
3.3 Estimation results

First stage and second stage. Table 1 reports the main estimation results from the first-stage probit regression. The results confirm that disability status has a statistically significant negative effect on the likelihood of employment relative to non-disabled individuals. Specifically, moderate (severe) disability is associated with a 10.55 (30.69) percentage point reduction in the probability of employment. When marginal effects are evaluated at the mean values of the other covariates, the corresponding reductions are 13.13 percentage points for moderate disability and 36.76 percentage points for severe disability. The one-year lagged time allocated to household errands is strongly and negatively correlated with the employment decision, supporting its relevance as an exclusion restriction².

The second-stage coefficients from the Heckman selection model are reported in Table 2. The coefficient on the inverse Mills ratio is 0.0800 with a clustered standard error of 0.0544, a ratio of 1.47, and a two-step bootstrap standard error of 0.0760 that is larger still. The point estimate is positive, which is the sign that positive selection into employment would imply, but it is not statistically distinguishable from zero.

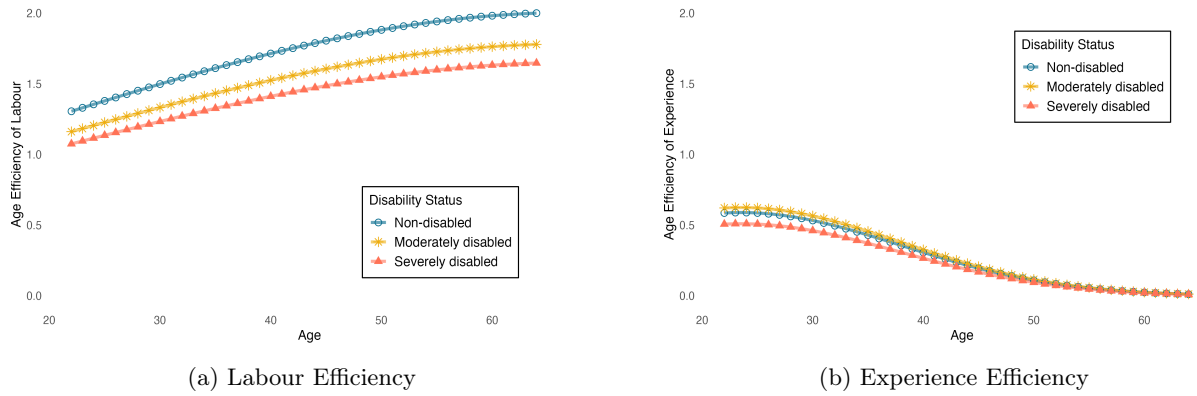
²Further details on the instrument diagnostics, including Wald tests of instrument relevance and of the exclusion restriction, are provided in Appendix A.4.

Figure 5: Life-cycle Profiles of Labour and Experience Efficiencies: Non-university Cohort



Notes: The panels plot $\hat{\lambda}_L(j, dis)$ and $\hat{\lambda}_E(j, dis)$ for non-university individuals.

Figure 6: Life-cycle Profiles of Labour and Experience Efficiencies: University Cohort



Notes: The panels plot $\hat{\lambda}_L(j, dis)$ and $\hat{\lambda}_E(j, dis)$ for university individuals.

We therefore do not claim to detect selection on unobservables. The correction is nevertheless retained, for two reasons. It is the specification of the wage equation we are replicating, so dropping it would change the object being estimated; and because the estimate is small, retaining it costs almost nothing, as the side-by-side comparison with the uncorrected model in Appendix A.4 confirms.

Moderate and severe disability reduce labour efficiency by 12.33% and 17.30% on average, relative to non-disabled workers with the same education. The effects are similar across education groups: moderate disability lowers labour efficiency by 13.60% for non-university workers and 11.05% for university workers, and severe disability by 16.94% and 17.65%. The effects on experience efficiency are quite different, and they are where the two severity levels part company. Moderate disability is associated with a positive effect in both education groups³, an increase of 4.94% for non-university workers and 6.06% for university workers, or 5.50% on average. Severe disability instead reduces experience efficiency sharply, by 31.64% for non-university workers and 13.46% for university workers, or 22.55% on average. The contrast between the two severity levels is the central estimate of this section. Moderate disability lowers the level of productivity without impairing the return to experience; severe disability lowers both, and it lowers the return to experience by more than it lowers labour efficiency. Because the two education groups differ so much in the severe state, with a 32% experience-efficiency penalty for non-university workers against 13% for university workers, the compounding cost of severe disability falls disproportionately on workers without a degree.

Because the decomposition is model-based, the estimated labour and experience efficiency profiles depend on the assumed functional form, the normalisations for the non-disabled group, and the maintained separation between current labour input and accumulated experience. The estimates are therefore best interpreted as disciplined wage decompositions that summarize how disability shifts different components of wage determination, rather than as direct observations of underlying productivity.

Using the estimated coefficients for age effects and disability-scaling factors, Figure 5 depicts the life-cycle efficiency profiles for non-university individuals, who typically join the labour market at age 18. The left panel shows that labour efficiency rises gently and almost linearly with age for all disability groups, with moderately and severely disabled workers on uniformly lower profiles throughout the working life. The right panel shows that experience efficiency declines steadily with age for all groups, reflecting decreasing returns to additional years of experience, and the disability gaps here take a different shape from those in the left panel. Moderately disabled workers sit slightly above the non-disabled, consistent with their positive estimated effect on experience efficiency, while severely disabled workers sit well below at younger ages, with the gap narrowing as all three profiles decline towards zero. The estimated effects behind both panels are documented in Table 2.

Figure 6 illustrates the life-cycle efficiency profiles for university-educated individuals, who typically enter the workforce around age 22 following graduation. Labour efficiency is higher in magnitude overall and exhibits continued improvements into the middle life cycle, reflecting the ongoing productivity returns to cognitive skills in graduate occupations. Severely disabled university workers exhibit labour efficiency profiles below the non-disabled, consistent with the estimated penalty of 17.65% for that group. Moderately disabled

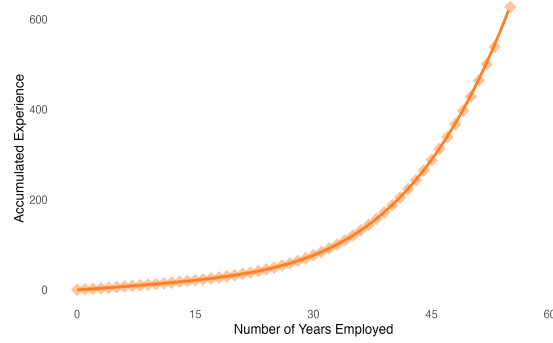
³The positive experience-efficiency effect for moderately disabled workers may reflect positive selection among those who remain employed, particularly into occupations where accumulated skills and work experience are more important and where moderate health limitations are less restrictive. The relative efficiency parameters reported in the lower panel of Table 2 show that experience efficiency receives a higher return than pure labour efficiency in three of the four disability-education cells, with estimates of 1.21 and 1.19 for moderately disabled non-university and university workers and 1.05 for severely disabled university workers. The exception is severely disabled non-university workers, whose estimate of 0.82 is below one: for that group a year of accumulated experience is worth less at the margin than the pure labour input it accompanies. The parameter declines with severity within both education groups, from 1.21 to 0.82 among non-university workers and from 1.19 to 1.05 among university workers, which says that disability reduces not only how much experience is accumulated but the wage return attached to it.

Table 2: Second-stage Non-linear Regression Results

Labour			Disability		
<i>Non-university</i>			<i>Non-university</i>		
$\lambda_{L,1}$	0.0068	(0.0047)	$\ln \phi_L(MD, LE)$	-0.1462**	(0.0452)
$\lambda_{L,2}$	0.0000	(0.0001)	$\ln \phi_L(SD, LE)$	-0.1856*	(0.0734)
<i>University</i>			<i>University</i>		
$\lambda_{L,0}$	0.1878***	(0.0325)	$\ln \phi_L(MD, HE)$	-0.1171	(0.0599)
$\lambda_{L,1}$	0.0205***	(0.0051)	$\ln \phi_L(SD, HE)$	-0.1942*	(0.0910)
$\lambda_{L,2}$	-0.0002	(0.0001)	Accumulated Experience		
Experience			γ_1	0.0477	(0.0494)
<i>Non-university</i>			γ_2	-0.0028	(0.0026)
$\lambda_{E,1}$	-0.0473*	(0.0220)	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>		
$\lambda_{E,0}$	-0.6023**	(0.2082)	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2146***	(0.1518)
$\lambda_{E,1}$	0.0266	(0.0258)	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8231**	(0.2537)
$\lambda_{E,2}$	-0.0024***	(0.0006)	<i>University</i>		
Inverse Mills Ratio			$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1924***	(0.2811)
0.0800	(0.0544)		$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0510**	(0.3997)
Sample Size			Weighted R^2	0.2706	
108,702					

Notes: The second-stage equation controls for state-specific linear time effects, and wave-specific dummies for marital status, years of schooling and gender. The dependent variable, wage, is adjusted for CPI and the indices are provided in Appendix A.2. Individual sample weights are used, with clustered standard errors denoted in parentheses. Significance levels are given as follows: ***p<0.001, **p<0.01, *p<0.05.

Figure 7: Cumulative Experience Function



Notes: This figure plots the non-linear accumulated experience function, $\hat{g}(e)$.

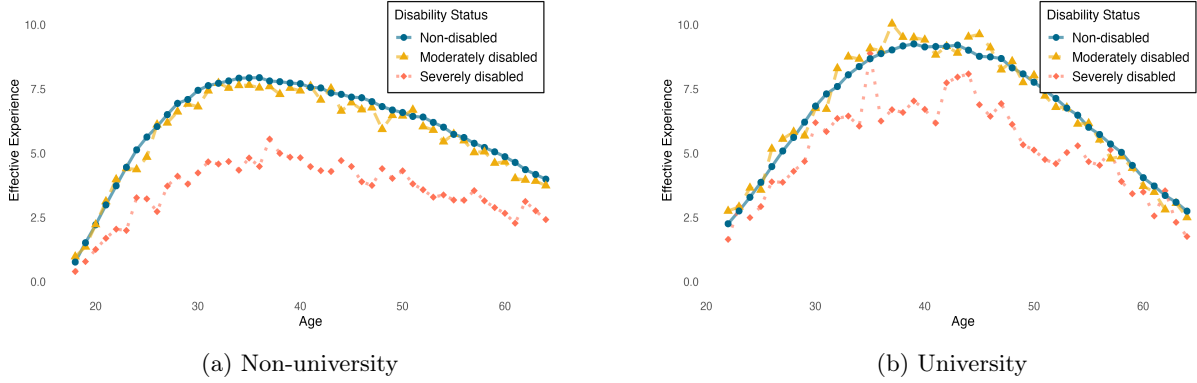
university workers exhibit higher experience efficiency than the non-disabled. This finding is consistent with Kim and Rhee (2022) and may reflect positive selection into experience-intensive roles among employed individuals with moderate disability, where occupation-specific knowledge partially compensates for reduced physical capacity.

Figure 7 demonstrates the second component of effective experience, the non-linear cumulative experience function $\hat{g}(e)$, where accumulated experience increases with years of employment. When combined with the first component, the experience efficiency profile $\hat{\lambda}_E(j, dis)$, the resulting effective experience is shown in Figure 8. In the early stages of the life cycle, the accumulation of work experience more than compensates for the rapid decline in experience efficiency. As individuals age, however, this accumulation only partially offsets the reduction in efficiency, producing a declining profile in later stages. Among workers with severe disability, whose employment rates and hours worked are substantially lower, this compensation mechanism is weaker: the reduction in labour market participation curbs experience accumulation, widening the effective experience gap relative to non-disabled workers over the course of the career.

Overall, labour efficiency carries greater weight than experience efficiency in determining productivity, particularly among highly-educated individuals, where pure labour effort contributes more substantially to efficiency over the life cycle. However, when accumulated experience from labour market participation is incorporated through the non-linear cumulative function, effective experience consistently exhibits larger magnitude than labour efficiency across both education groups. This pattern underscores the substantial endowment of accumulated work experience relative to pure labour input, highlighting the critical role of sustained employment in building long-run productive capacity. For disabled workers who face substantially lower employment rates and shorter work histories, this implies a compounding disadvantage: the direct reduction in labour efficiency combines with curtailed experience accumulation to widen the productivity gap progressively over the career.

Decomposition of productivity. We integrate the estimated efficiency schedules, accumulated experience, relative prices and other regressors, to decompose productivity into two components, the labour component and the experience component. This decomposition is economically informative: a disability gap concentrated in the labour component reflects a direct reduction in productive capacity, while a gap driven

Figure 8: **Life-cycle Profiles of Effective Experience**



Notes: The panels plot $\hat{\lambda}_E(j, dis) \cdot \hat{g}(e)$ by education.

by the experience component may be partially addressable through policies that support sustained labour market participation.

Equation 2 can be rewritten as

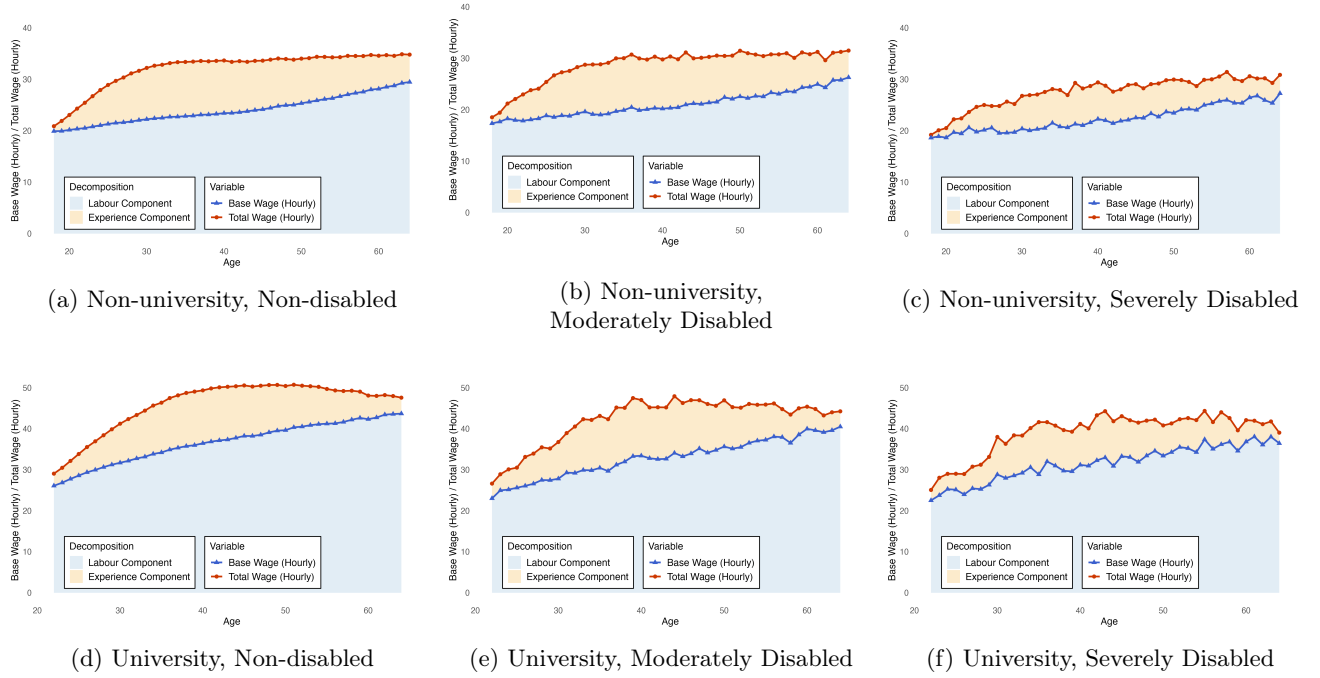
$$\hat{w}_{it}(j, dis, e, edu) = \hat{z}_{it} \cdot \hat{R}_{L_t} \cdot \hat{\lambda}_L(j, dis_{it}, edu_{it}) \cdot \left[1 + \frac{\hat{R}_{E_t}}{\hat{R}_{L_t}} \cdot \frac{\hat{\lambda}_E(j, dis_{it}, edu_{it})}{\hat{\lambda}_L(j, dis_{it}, edu_{it})} \cdot \hat{g}(e) \right], \quad (5)$$

where the first term, $\hat{z}_{it} \cdot \hat{R}_{L_t} \cdot \hat{\lambda}_L(j, dis_{it}, edu_{it})$, is denoted as the base wage or the labour component, and the second term within the square brackets is defined as the experience multiplier. The experience component is then computed as the difference between total productivity and the base wage, expressed as $\hat{z}_{it} \cdot \hat{R}_{E_t} \cdot \hat{\lambda}_E(j, dis_{it}, edu_{it}) \cdot \hat{g}(e)$.

Figure 9 presents the decomposition of productivity into labour and experience components across the age profile, stratified by educational attainment and disability status. The top panels show results for the non-university cohort, while the bottom panels correspond to the university cohort. The figures reveal that individuals with disabilities exhibit lower total productivity at all ages relative to non-disabled workers of the same education, with the productivity shortfall largest for severely disabled workers.

The labour component (base wage), the blue shaded region, accounts for most of productivity at every age, and for 76% to 87% of it in the first few years after labour market entry. The experience component, the light-red region, follows a hump shape rather than rising monotonically. It grows steeply through the twenties and early thirties, peaks in the mid to late thirties, and then declines for the rest of the working life. For non-disabled non-university workers it reaches 32% of total productivity at age 34 and falls back to 15% by age 64; for their university-educated counterparts it peaks lower, at 27% around age 39. The hump comes from the two terms that build the experience component pulling in opposite directions: accumulated experience keeps rising with years worked, while experience efficiency declines with age, and after the mid-thirties the second effect dominates. The experience share is larger for non-university workers than for university workers at almost every age, which is the sense in which experience matters more for pay in that group. Disability compresses both components. For moderate disability the experience share is if anything slightly higher

Figure 9: **Life-cycle Profiles of Predicted Productivity**



Notes: The base wage and total wage in all panels, expressed in 2018-2019 prices, are computed as the mean values across each combination of disability and education.

than for the non-disabled, peaking at 34%, so the wage penalty operates almost entirely through the level of labour efficiency. For severe disability the experience share is lower at every age, peaking at 27% among non-university workers, which reflects the 32% experience-efficiency penalty estimated for that group.

These results indicate that disability affects lifetime productivity through two reinforcing channels. First, lower labour efficiency directly reduces wages at all ages. Second, lower employment rates slow the accumulation of work experience, causing the experience component of wages to grow more slowly and widening the initial productivity gap over time. This compounding mechanism is particularly pronounced among non-university workers, whose earnings rely more heavily on accumulated experience later in their careers. The findings highlight the importance of policies that not only improve access to employment but also promote sustained labour market attachment, as accumulated work experience plays a key role in the widening disability earnings gap over the life cycle.

The empirical facts and wage decompositions are informative about where disability-related productivity gaps arise, but they are not sufficient for evaluating how these gaps translate into labour market activity, earnings and resources across groups over the full life cycle. Employment, hours, experience accumulation, taxes and transfers interact dynamically, so the observed cross-group gaps do not directly reveal the lifetime consequences of disability or the role of Australian institutions. The next section therefore embeds the estimated productivity profiles in a structural life-cycle model, allowing us to simulate labour supply, earnings, net income and consumption for each disability and education group under the benchmark economy and policy counterfactuals.

4 Simulation

In this section, we develop a structural life-cycle model that incorporates the disability- and education-specific productivity profiles estimated in the empirical analysis. The model provides a framework for quantifying how disability affects labour supply, program participation, lifetime earnings, and welfare over the life cycle. We calibrate the benchmark economy to key Australian demographic, labour market, and tax-and-transfer moments. The benchmark economy is solved in general equilibrium, jointly determining labour supply, earnings, consumption, and fiscal balance. We then conduct partial-equilibrium counterfactuals to isolate the direct effects of productivity and policy changes on household labour supply and earnings.⁴

4.1 Environment

Demographics. Individuals enter the model at $j = 1$, remain in the labour force until age $j = J_w$, and live in retirement until the maximum age $j = J$. Individuals of age j face an exogenous survival probability ψ_j in each period, and leave behind warm-glow bequests due to the mortality risk. The measure of age- j individuals at time t is given by $\mu_j = \frac{\mu_{j-1}\psi_j}{1+n}$, where n is the population growth rate.

Preferences. The utility function is given by $u(c_j, \tilde{l}_j)$, which depends on consumption c_j and effective leisure $\tilde{l}_j = 1 - m_h(\varepsilon_D, \varepsilon_E)n_j - \bar{n}_j(\varepsilon_D, \varepsilon_E) \cdot 1_{[0 < n_j]}$. Working reduces effective leisure through two channels. Each hour of work n_j carries a type-specific work-hour disutility weight $m_h(\varepsilon_D, \varepsilon_E)$, so the same hours are more costly in utility terms for a type with a higher weight, and any positive amount of work incurs a fixed participation cost $\bar{n}_j(\varepsilon_D, \varepsilon_E)$, which varies with age, disability status, and education type. The indicator

⁴The dynamic general equilibrium framework also allows us to evaluate implications for aggregate economic outcomes and social welfare.

function is defined as $1_{[0 < n_j]} = 1$ and $1_{[0 = n_j]} = 0$. Future utility is discounted by the factor β , and individuals derive additional utility from leaving bequests, represented by the function $b(a_j)$, which is assumed to be increasing in terminal wealth a_j .

Endowments. In each period, the individual is endowed with one unit of time that can be spent on market work n_j or leisure l_j . Labour productivity is composed of a deterministic component and a stochastic component. The deterministic component $e_{j,\varepsilon_D,\varepsilon_E}$ depends on age, permanent disability status and education type. The stochastic component captures idiosyncratic labour productivity risk. Let $z_j \in Z = \{1, 2, 3\}$ denote the productivity state at age j . The productivity state evolves according to a first-order Markov process with transition probabilities $\pi_z(z_{j+1}|z_j)$, and each state maps into a realised multiplicative productivity factor $\eta(z_j)$. Hence, the before-tax labour income of an individual of age j , disability status ε_D , education type ε_E and productivity state z_j is given by $\eta(z_j)e_{j,\varepsilon_D,\varepsilon_E}(1 - l_j)w$, where w is the market wage rate.

Technology. We assume a representative firm that operates within a competitive environment, employing capital K and effective labour H as inputs. The firm exhibits a constant returns to scale production technology, where output Y is given by the functional form $Y = AK^\alpha H^{1-\alpha}$, where $A \geq 0$ represents total factor productivity, and $\alpha \in (0, 1)$ denotes the capital share of output. Capital depreciates at a constant rate $\delta \in (0, 1)$ per period. The firm selects optimal levels of capital and effective labour to maximise its profit, given the wage rate w for labour and the rental rate q for capital. The profit maximisation problem is stated as $\max_{K,H} AK^\alpha H^{1-\alpha} - qK - wH$.

Taxes and transfers. The government collects a progressive labour income tax on taxable income y_j , denoted by $\text{tax}(y_j)$, as well as a consumption tax τ_c . These tax revenues finance transfer programs, including the Disability Support Pension (dsp) and the Age Pension (pension). Individuals below the Age Pension eligibility age J_w who have a disability, satisfy the hours rule, and meet the means tests criteria are eligible to receive DSP benefits. Upon reaching age J_w , all individuals become eligible for the Age Pension, which is subject to the standard means tests. In the steady state, the government budget constraint is given by

$$\sum_j \text{tax}(y_j) + \tau_c \sum_j c_j + D' = G + \sum_j \text{pension}_j + \sum_j \text{dsp}_j + (1 + r)D, \quad (6)$$

where D' denotes new debt issuance, D is previous debt stock, and G is government consumption.

Market structure. Markets are incomplete. Individuals cannot insure against idiosyncratic productivity risk or mortality risk through state-contingent assets. Borrowing constraints prevent negative asset holdings, requiring $a \geq 0$. The economy is assumed to be a small open economy in which the domestic capital market is perfectly integrated with the world capital market. Capital flows freely into and out of the economy, and the domestic interest rate r is therefore exogenous. Labour is internationally immobile, with no migration permitted. Because the interest rate is fixed by the world capital market and the technology has constant returns to scale, the firm's first-order conditions pin down the capital-labour ratio and hence the wage rate w : the wage follows from the production side of the economy and does not respond to aggregate labour supply.

4.2 Household problem

Workers. The state vector of the working individual is $x_j = \{a_j, z_j, \varepsilon_D, \varepsilon_E\} \in [a_{\min}, a_{\max}] \times \{1, 2, 3\} \times \{1, 2, 3\} \times \{1, 2\}$, where a_j denotes current assets, z_j represents the productivity shock, ε_D is the permanent disability status, and ε_E is the permanent education type. After the realisation of the productivity shock, individuals choose consumption, leisure, and next-period assets over the bounded alternatives described below: $\vartheta_j \equiv \{(c_j, l_j, a_{j+1}) \in R^{++} \times [0, 1] \times [a_{\min}, a_{\max}]\}$, where c_j is consumption, l_j is leisure, and a_{j+1} is savings or future assets.

The optimisation problem for the working individual can be recursively expressed as

$$V(\chi_j) = \max_{\vartheta_j} \left\{ u(c_j, \tilde{l}_j) + \beta \left[\psi_{j+1} \sum_{z_{j+1}} \pi_z(z_{j+1}|z_j) \cdot V(\chi_{j+1}) + (1 - \psi_{j+1}) \cdot b(a_{j+1}) \right] \right\}, \quad (7)$$

subject to

$$(1 + g)a_{j+1} = \overbrace{ra_j + \eta(z_j)e_{j,\varepsilon_D,\varepsilon_E}(1 - l_j)w}^{\text{Market income } (y_j^m) \text{ or taxable income } (y_j)} + \text{dsp}_j - \text{tax}(y_j) + \text{beq}_j + a_j - (1 + \tau_c)c_j, \quad (8)$$

where β is the time discount factor, r is the interest rate, dsp_j is the DSP benefit and beq_j is the lump-sum bequest transfer. Consumption is purchased at the tax-inclusive price $(1 + \tau_c)$, and next-period assets are scaled by the trend growth rate g of GDP per capita, which expresses them in current-period units along the balanced growth path. Market income y_j^m or taxable income y_j combines capital income ra_j and labour income $\eta(z_j)e_{j,\varepsilon_D,\varepsilon_E}(1 - l_j)w$, which is used to compute taxes payable.

Public taxation includes consumption taxes and income taxes. Consumption is taxed at the rate τ_c , so that the consumption tax paid by individual j is $\tau_c c_j$. Following [Tran and Zakariyya \(2022\)](#), the progressive income tax function is specified as $\text{tax}(y_j) = \max\{0, y_j - \lambda y_j^{1-\tau_y}\}$, which depends on the taxable income y_j . The parameters λ and τ_y represent the scale and curvature of the income tax function, respectively. The Age Pension is included in taxable income, while the DSP is not taxed.

In the model, the DSP is the sole social security program available to working-age individuals. The eligibility criteria for the DSP, comprising age requirement, medical and non-medical tests, can be represented by the indicator function $1_{[j < J_w \wedge \varepsilon_D \in \{3\} \wedge (1 - l_j) \cdot \bar{h}^w \leq \bar{h}]}$, where $\bar{h}^w$ denotes the actual hours per week and $\bar{h}$ represents the maximum hours threshold. Individuals with disability types $\varepsilon_D \in \{3\}$ satisfy the medical eligibility requirement, while those working fewer than or equal to $\bar{h}$ hours per week meet the non-medical (hours) test. The DSP is subject to means tests. Following [Kudrna, Tran and Woodland \(2022\)](#), the pension payable under the income test, denoted dsp^y , can be summarised as

$$\text{dsp}^y = \begin{cases} p^{\max} & \text{if } y^m \leq \bar{y}_1 \\ p^{\max} - \omega^y(y^m - \bar{y}_1) & \text{if } \bar{y}_1 < y^m < \bar{y}_2 \\ 0 & \text{if } y^m \geq \bar{y}_2 \end{cases} \quad (9)$$

with $p^{\max}$ denoting the maximum benefit, y^m representing the market income, $\bar{y}_1$ capturing the maximum pension threshold, $\bar{y}_2$ denoting the zero pension threshold, and ω^y specifying the taper rate. Qualified individuals receive full pension if their income is below the cut-off point for full pension. Otherwise, levels over the thresholds reduces pension at the taper rate. If income exceeds the cut-off point for zero pension, individuals receive no pension. The same equation structure applies to the assets test, yielding dsp^a . The actual DSP benefit received by individual j is then $\text{dsp}_j = \min\{\text{dsp}^y, \text{dsp}^a\}$.

Retirees. Individuals retire at $j = J_w$, cease market work for the remainder of their lives, and become eligible for the Age Pension. The state space of the retired individual is given by $x_j = \{a_j, \varepsilon_D, \varepsilon_E\} \in [a_{\min}, a_{\max}] \times \{1, 2, 3\} \times \{1, 2\}$. The optimisation problem for the retired individual is then reduced to

$$V(\chi_j) = \max_{\{c_j, a_{j+1}\}} \left\{ u(c_j) + \beta \left[\psi_{j+1} \cdot V(\chi_{j+1}) + (1 - \psi_{j+1}) \cdot b(a_{j+1}) \right] \right\}, \quad (10)$$

subject to

$$(1 + g)a_{j+1} = \overbrace{ra_j + \text{pension}_j}^{\text{Taxable income } (y_j)} - \text{tax}(y_j) + \text{beq}_j + a_j - (1 + \tau_c)c_j, \quad (11)$$

where taxable income consists of capital income ra_j and the Age Pension benefit pension_j , which is subject to means tests with the same structure as the DSP tests, evaluated at the statutory Age Pension rates.

4.3 Mapping the model to data

The calibration combines inputs from HILDA, policy parameters, and externally calibrated parameters from the Australian literature. The deterministic labour productivity profiles are taken from the empirical wage estimates in Section 3. Initial asset holdings, survival probabilities, the initial distributions of education and disability, and the age-specific joint distribution of education and disability are constructed from HILDA and ABS Life Tables. The type-specific work-hour disutility weights and participation-cost schedules are calibrated to reproduce life-cycle employment and hours profiles by education and disability status, and the DSP schedule multiplier and the severe-disability work-cost terms are calibrated to the age profile of DSP receipt. The tax-function scaling parameter adjusts endogenously to satisfy the government budget constraint in the benchmark equilibrium. Policy parameters for the Age Pension, the DSP, the income and assets tests, and the consumption tax are taken from Australian institutional settings and expressed in model units using the benchmark tax-function scale. The idiosyncratic productivity process is estimated from the paper's own second-stage wage residuals. The remaining parameters, including those governing bequests, the progressive income tax curvature, and aggregate technology, are taken from the literature or set to standard values used in Australian applications. The model's income units are converted back to annual dollars using reference labour income at age 50 from HILDA. A complete list is presented in Table B.1.

Demographics and preferences. One model period corresponds to one calendar year. Individuals are assumed to live $J = 69$ periods, from $j = 1$ (age 22) to $j = 69$ (age 90). Starting from $J_w = 44$ (age 65), individuals are forced to retire and become eligible to receive Age Pension benefits. The survival probabilities, denoted by ψ_j , are age-dependent and are estimated using data from the Australian Life Tables. The population growth rate n is set to 1.4% per annum, consistent with the long-run average annual growth rate of the Australian population over the period 1971-2021 as reported by the Australian Bureau of Statistics (ABS). The period utility function is specified as

$$u(c_j, \tilde{l}_j) = \frac{\left[c_j^\gamma \tilde{l}_j^{1-\gamma} \right]^{1-\sigma}}{1-\sigma} \quad , \quad \tilde{l}_j = 1 - m_h(\varepsilon_D, \varepsilon_E) n_j - \bar{n}_j(\varepsilon_D, \varepsilon_E) \cdot 1_{[0 < n_j]} \quad (12)$$

The preference weight on consumption, γ , and the curvature parameter, σ , are set to 0.344 and 3.694, respectively, and discipline the model's life-cycle labour supply response. The work-hour disutility weight $m_h(\varepsilon_D, \varepsilon_E)$ is a single calibrated number for each of the six education-disability types. The fixed cost of workforce participation $\bar{n}_j(\varepsilon_D, \varepsilon_E)$ varies by age, education, and disability status. It combines a baseline schedule that is linear in age for each type with a piecewise-linear adjustment anchored at ages 22, 43, and 64, whose knots are calibrated jointly with the disutility weights to reproduce the life-cycle employment and average-hours profiles observed in HILDA; the combined schedule is floored at zero, so a participation cost can never become a participation subsidy. For the severely disabled, the schedule contains an additional level and age-slope term, calibrated together with the DSP schedule multiplier to the age profile of DSP receipt. Weekly hours are chosen from a discrete menu covering zero, 4 to 25 hours in one-hour steps, and 35, 40 and 60 hours, expressed as shares of a 168-hour week, with dense coverage around the statutory 15-hour DSP threshold. The discount factor is set to $\beta = 0.996$ per annum, a standard value at this frequency; it is not calibrated to a moment of its own.

The bequest function follows that of [De Nardi \(2004\)](#), which is given by $b(a_j) = \phi_1 \left(1 + \frac{a_j}{\phi_2} \right)^{1-\sigma}$, where ϕ_1 represents the intensity of the bequest motive, and ϕ_2 determines the degree of luxury associated with bequests. The parameter values are set to $\phi_1 = -9.5$ and $\phi_2 = 11.6$, consistent with calibrated values reported in the existing literature.

Endowments. Labour productivity at age j is denoted by $\eta(z_j) e_{j, \varepsilon_D, \varepsilon_E}$, which depends on age j , the idiosyncratic labour productivity shock state z_j , disability type ε_D , and education level ε_E . The deterministic component $e_{j, \varepsilon_D, \varepsilon_E}$ is obtained from the empirical estimation in Section 3 and gives the age-specific labour-efficiency profile for each education-disability group. The stochastic component $\eta(z_j)$ captures idiosyncratic productivity shocks, where the underlying latent log-productivity process $\tilde{z}_j$ evolves according to the $AR(1)$ process

$$\tilde{z}_j = \rho \tilde{z}_{j-1} + \eta_j, \quad \eta_j \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, \sigma_\eta^2), \quad (13)$$

with innovation η_j . The latent process $\tilde{z}_j$ is discretised into three productivity states, $z_j \in \{1, 2, 3\}$, corresponding to realised productivity factors $\eta(z_j) \in \{\eta_L, \eta_M, \eta_H\}$. The transition probabilities are con-

structed using the [Tauchen \(1986\)](#) method, generating an age-invariant Markov chain with transition matrix $\pi_z(z_{j+1}|z_j)$. The three realised productivity factors follow from the same discretisation and are normalised so that their stationary mean equals one, so the shock moves wages around the deterministic profile without changing its level. The persistence parameter $\rho = 0.8076$ and the innovation variance $\sigma_\eta^2 = 0.0134$ are estimated from the second-stage wage residuals of the wage equation in Section 3, which is the same source as the deterministic productivity profiles. Estimating the process here rather than importing it from the literature keeps the stochastic and deterministic parts of productivity on the same footing: both come from the same wage equation and the same sample.

Disability is classified into three categories, $\varepsilon_D \in \{\text{ND}, \text{MD}, \text{SD}\}$, corresponding to non-disabled, moderately disabled, and severely disabled, respectively. Education level is defined as $\varepsilon_E \in \{\text{LE}, \text{HE}\}$, corresponding to non-university and university education. These classifications are consistent with those used in the empirical analysis. At the entry age $j = 1$, the marginal distributions are taken from HILDA and equal $\mu_{j=1}^{\varepsilon_E} = \{0.81, 0.19\}$ for education and $\mu_{j=1}^{\varepsilon_D} = \{0.92, 0.05, 0.03\}$ for disability. Entrants draw the joint education-disability state from its empirical joint distribution, so the dependence between education and disability at entry is preserved, and draw their initial productivity state from the stationary distribution of the shock process. Because both permanent types are fixed after entry and survival is common across types, the model's age composition of types follows from this entry distribution. The observed age-dependent joint distributions $\mu_j^{\varepsilon_E, \varepsilon_D}$ derived from the HILDA survey are therefore used as reporting weights: whenever type-specific moments are aggregated, most importantly for the DSP participation profile, model moments are compared with the data at the observed age-specific composition of education and disability. Assuming that only individuals with $\varepsilon_D = \text{SD}$ (severely disabled) satisfy the medical eligibility criteria for the DSP, these weights, combined with the assumed medical test, allow the model's DSP recipient ratio to be matched to its HILDA counterpart.

Initial asset holdings at age 22 ($j = 1$) are computed from individuals observed at that age in the HILDA Survey. Net wealth is defined comprehensively to include own and joint bank account balances, superannuation holdings, minus own and joint credit card debt, HECS-HELP debt, and other personal debts. Negative assets are truncated at zero to comply with the model's no-borrowing constraint $a \geq 0$. The top of the distribution is winsorised at the weighted 99.5th percentile, so that no single respondent determines its scale. The weighted observations are then smoothed with a Gaussian kernel onto a 500-point grid whose support is expressed in real 2018-2019 dollars, yielding the initial distribution $\mu_{j=1}^a$. The dollar support is converted into model asset units with the same endogenous scale used for the pension and DSP schedules, and the conversion is refreshed whenever that scale updates during the equilibrium iteration, so all monetary inputs share a single unit convention.

Technology and market structure. The aggregate production function is Cobb-Douglas: $Y = AK^\alpha H^{1-\alpha}$. Following [Tran and Woodland \(2014\)](#), the capital share of income is set to $\alpha = 0.35$, total factor productivity is normalised to $A = 1$, and the depreciation rate is set to $\delta = 0.05$. Consistent with [Kudrna, Tran and Woodland \(2022\)](#), the long-run growth rate of GDP per capita is set to $g = 1.6\%$ per annum, reflecting the historical average growth rate observed in Australia from the early 2000s onward. The economy is assumed to be small and open, so the domestic real interest rate is exogenous and set to $r = \bar{r} = 2\%$ per annum.

Taxes and transfers. The tax-and-transfer system is calibrated to reflect Australian fiscal policy. The consumption tax rate is set to the Australian Goods and Services Tax (GST) rate of $\tau_c = 10\%$, as reported by the Australian Tax Office (ATO). Following [Tran and Zakariyya \(2022\)](#), the curvature parameter of the

progressive income tax function τ_y is set to 0.15. The income test taper rate ω^y is 0.5 (i.e., 50 cents per dollar of private income above the threshold), and the asset test taper rate ω^a is 0.003, corresponding to a 3-dollar reduction in benefits per thousand dollars of assets above the threshold. The scaling factor of the tax function λ is internally calibrated to ensure government budget balance in the benchmark steady state. The remaining parameters, including the hours threshold $\bar{h}$, the maximum pension $p^{\max}$, and the full pension threshold $\bar{y}_1$, are expressed in consistent model units and are sourced from Services Australia. One DSP parameter is internal: the DSP maximum payment and its means-test thresholds are scaled together by a single calibrated multiplier, which preserves the statutory ratios between the payment and the thresholds while matching the observed level of DSP take-up.

Model performance. The benchmark model is calibrated to reproduce key Australian life-cycle labour market profiles and aggregate moments. The main calibration targets are weekly labour hours and employment rates by education and disability status. These targets discipline the labour-supply margins through which the counterfactual experiments operate. We also report a third life-cycle moment, annual labour earnings by age and group, which the model is not calibrated to: the calibration parameters are already pinned down by hours and employment, so earnings serve as a check that combines both labour supply margins with the estimated wage structure.

Figure 10 compares the model-generated profiles with their empirical counterparts. The model tracks the life-cycle ranking of both average weekly hours and employment rates across disability groups in each education group, including the much lower labour supply of severely disabled workers. The model also reproduces the shape of each profile over the working life, including the decline in hours and employment after the mid-fifties. Appendix B.3 reports the fit group by group and discusses where the remaining error sits.

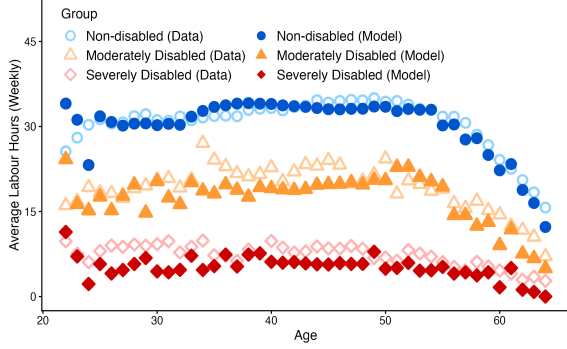
The bottom panel of Figure 10 reports the calibration of DSP participation over the working life. The model captures the broad age profile of DSP receipt, including the low rate of receipt at younger ages and the gradual increase through middle and later working ages. This fit is important because DSP receipt is disciplined jointly by severe-disability status, the hours rule, means testing, and the endogenous labour supply response. The fit deteriorates somewhat at later working ages, where the model tends to overstate observed DSP participation near the peak of receipt. This likely reflects the simplified treatment of program dynamics: the model does not explicitly include transitions between DSP receipt and the Age Pension, application behaviour, or persistence in benefit receipt. Overall, the calibration delivers a reasonable approximation of the DSP participation margin that is central to the counterfactual analysis.

Figure 11 turns to the earnings check. The model reproduces the level and ordering of annual labour earnings across the six groups, matching group means over ages 22 to 64 to within about 10 per cent for the three largest groups. The remaining error sits mostly in the shape of the profile late in working life, where the model's earnings peak earlier and decline faster than the data, the same ages at which the hours and employment fits are loosest. Appendix B.3 reports the errors group by group and explains why we do not recalibrate to close this gap.

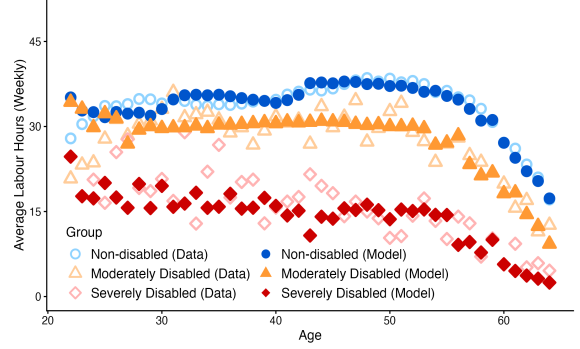
4.4 Simulation results

The benchmark model serves as the baseline for quantifying the economic costs of disability in the economy. We conduct two main counterfactual experiments: (i) removing the experience component from the production technology, and (ii) completely eliminating the DSP program. The first experiment quantifies

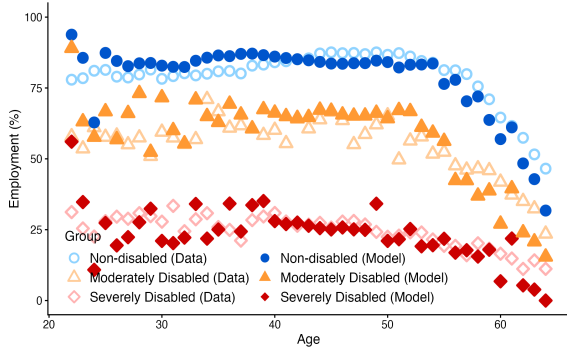
Figure 10: **Estimation Targets: Average Labour Hours (Weekly), Employment Rate, and DSP Participation Rate**



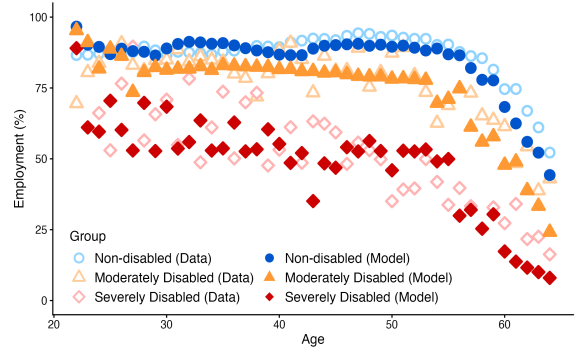
(a) Labour Hours: Non-university



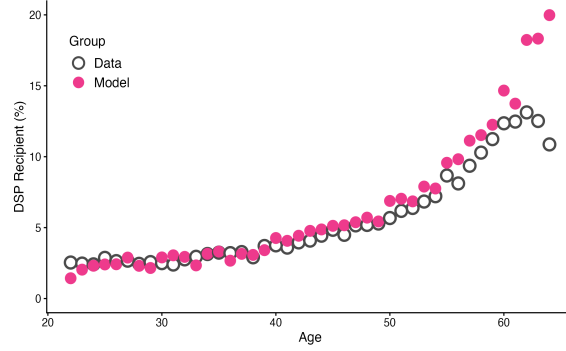
(b) Labour Hours: University



(c) Employment: Non-university



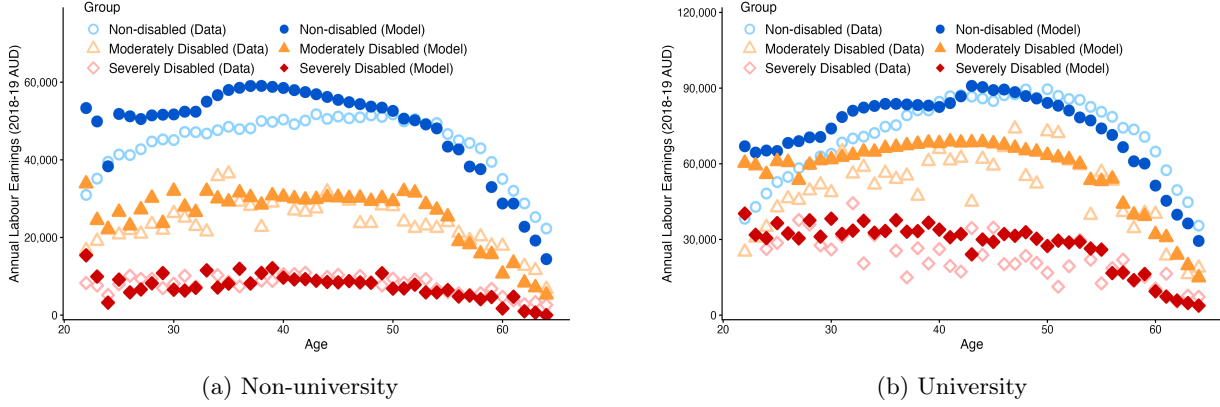
(d) Employment: University



(e) DSP Participation

Notes: The participation costs $\bar{n}_j(\varepsilon_D, \varepsilon_E)$ and the work-hour disutility multipliers are calibrated to match the life-cycle profiles of weekly hours and employment rates by education and disability status; the preference parameters σ and γ discipline the overall labour supply response. Model DSP receipt by type is aggregated using the observed age-specific education-disability composition; the DSP schedule multiplier and the severe-disability participation-cost level and slope are the parameters calibrated to this profile. The fit is weaker at older working ages because the model does not explicitly model transitions from DSP to the Age Pension.

Figure 11: Data VS Model: Annual Labour Earnings



Notes: Model and HILDA annual labour earnings by age, in real 2018-19 AUD. Both series are unconditional group means at each age, counting the non-employed at zero, so the comparison covers the extensive and the intensive margin together. Model earnings are converted from model units with the same exchange rate used for every other monetary outcome in the paper, which matches mean labour income at age 50 in the model to its HILDA counterpart. Earnings are not a fitted target.

the role of work experience as a distinct channel of human capital accumulation, identifying how much of each group's lifetime income depends on experience relative to pure labour efficiency. The second experiment evaluates the labour supply and income effects of the DSP, isolating the behavioural response to the removal of disability income support and measuring the extent of the program's work disincentive. For each experiment, we examine the resulting changes in life-cycle earnings profiles and lifetime income, with a particular focus on heterogeneity across disability states and education levels. The life-cycle labour earnings profiles are generated using forward simulations of 100,000 individuals. To reduce simulation noise in the comparison across policy environments, the benchmark, no-experience-component, and no-DSP specifications use the same simulated initial states, productivity shocks, survival draws, and asset-position draws.

Disability, lifetime income and decomposition. We report the benchmark results in the first three columns of Table 3. Moderate and severe disabilities substantially reduce lifetime labour earnings, net income and consumption. Relative to non-disabled workers with the same education, moderately disabled individuals earn 46.9% less lifetime labour income in the non-university group and 21.1% less in the university group. The losses for severely disabled individuals are far larger, at 84.4% and 60.5% respectively. Two features of these gaps deserve comment. First, they are much wider than a wage penalty alone would generate, because lifetime labour income combines the wage penalty with large differences in employment and hours: in the data the severely disabled work roughly a quarter as many hours per week as the non-disabled once non-workers are counted at zero, and the model is calibrated to reproduce that. Second, the severe category includes respondents who report that they cannot work at all, whose lifetime labour income is close to zero by construction, which is why the non-university severe gap approaches 85%. The gaps narrow considerably once taxes and transfers are applied. Lifetime net income for the severely disabled is 76.2% below the non-disabled level among non-university workers and 54.9% below it among university workers, and lifetime consumption is 74.7% and 53.7% below. Put the other way, severely disabled individuals consume 25.3% of the non-disabled lifetime amount among non-university workers and 46.3% among university graduates.

In the first counterfactual experiment, we remove the experience component from the productivity profile.

Table 3: **Experiment Results: Removal of the 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	1,434,467	1,104,772	897,796	-28.63%	-24.08%	-22.16%
Moderately Disabled	762,292	643,059	537,446	-32.91%	-26.71%	-24.98%
Severely Disabled	224,135	263,345	227,119	-31.56%	-19.40%	-18.79%
University						
Non-disabled	2,147,665	1,545,143	1,236,090	-22.50%	-18.96%	-17.72%
Moderately Disabled	1,694,729	1,261,185	1,010,154	-24.73%	-20.81%	-19.21%
Severely Disabled	848,369	696,977	572,483	-24.71%	-19.94%	-18.52%

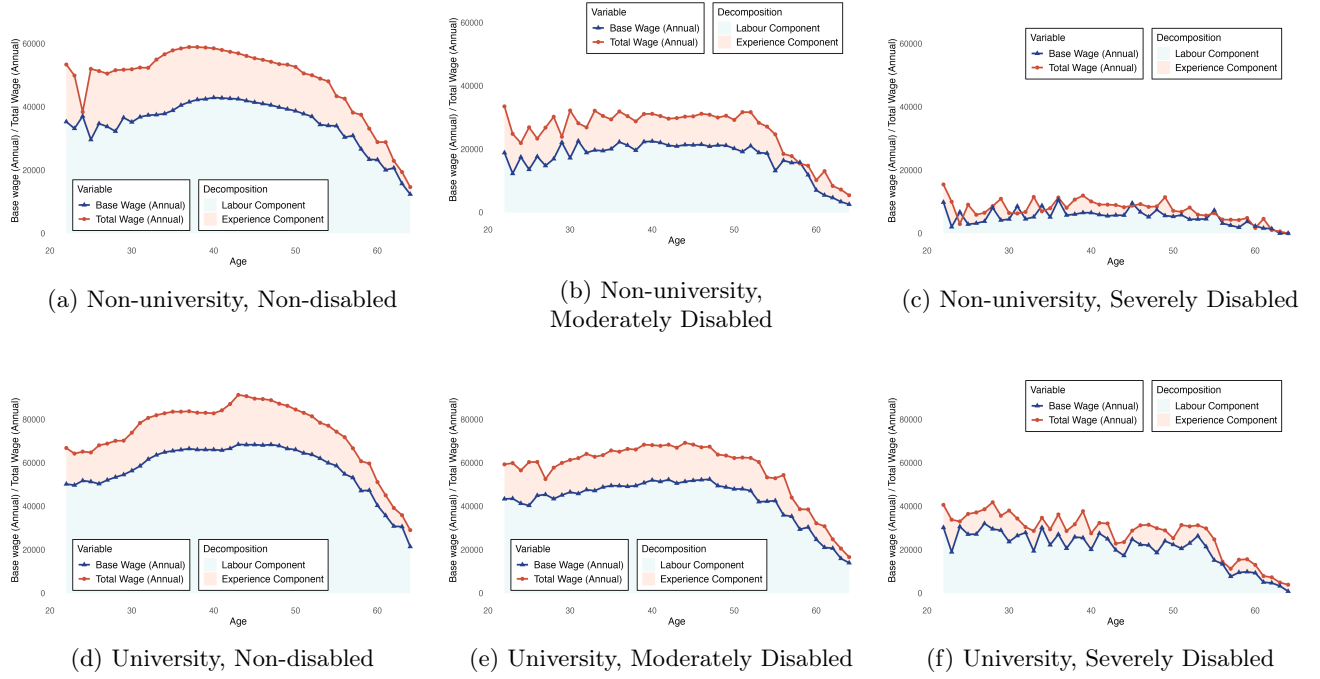
Notes: The first three columns report present-value lifetime labour income, net income and consumption in the benchmark calibration, disaggregated by disability status and education level. The last three columns report percentage changes relative to the benchmark when the experience component is removed from the productivity process. Monetary values are expressed in 2018-2019 prices. To convert model units into dollars, we compute the average labour income of 50-year-old agents in the HILDA Survey and divide it by the corresponding model-generated mean labour income. The resulting exchange rate is applied uniformly to all lifetime profiles.

Results are reported in the final three columns of Table 3. Lifetime labour income falls for every group, by between 22.5% and 32.9%. The clearest pattern is by education rather than by disability: all three non-university groups lose more than any university group. Within the non-university group the losses are 32.9% for the moderately disabled, 31.6% for the severely disabled and 28.6% for the non-disabled; within the university group they are 24.7% for both disability states and 22.5% for the non-disabled. Two things follow. The experience channel is worth more to non-university workers, whose pay depends more on accumulated experience than on formal qualifications, and within each education group it is worth more to workers with a disability than to those without one. Both are consequences of the same estimates: the labour-efficiency profile is flatter and lower for these groups, so a larger share of their pay comes from the experience term. The reductions in net income and consumption are generally less severe than those in gross labour income. This attenuation reflects the redistributive nature of Australia’s tax-and-transfer system, which lowers tax burdens and increases benefit receipt at lower income levels, thereby partially offsetting the loss in pre-tax earnings.

Figure 12 illustrates the implied life-cycle labour income profiles by disability status and educational attainment under the counterfactual. In all groups, the experience component accounts for a substantial share of total lifetime labour income. Its relative contribution is larger among non-university-educated individuals than among university-educated individuals. This pattern reinforces the conclusion that on-the-job human capital accumulation plays a more critical role in the earnings dynamics of less-educated workers, and that losing the experience channel compounds the disadvantage faced by workers with disabilities.

Importance of government support. The second experiment eliminates the Disability Support Pension. Results are presented in Table 4. For individuals with severe disabilities, the removal raises lifetime labour income: by 36.7% among non-university workers and by 6.7% among university workers. These gains reflect behavioural responses to the loss of benefits, whereby affected individuals raise labour force participation and hours worked to partly offset the foregone transfers. The gap between the two education groups is large, and

Figure 12: **Experiment Results: Removal of the Experience Component**



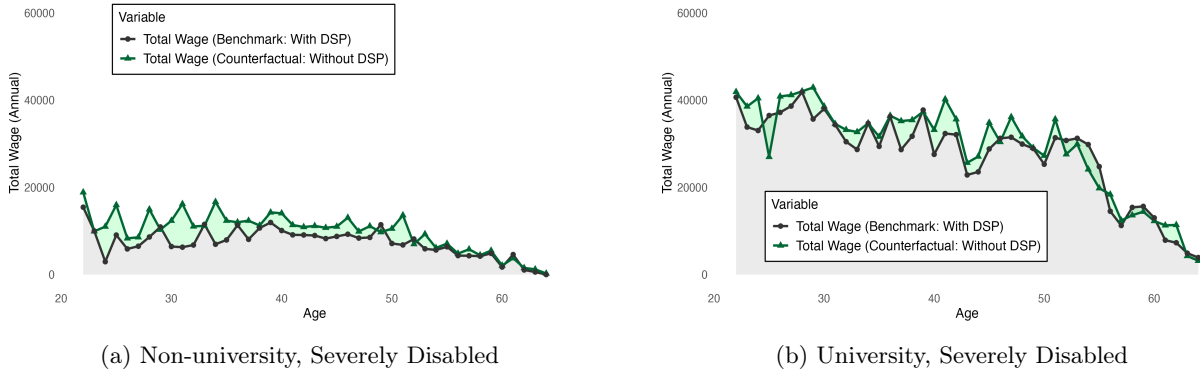
Notes: Annual labour earnings are reported in 2018-2019 prices. For each education-disability group, the profiles are simulated conditional group averages over surviving individuals at each age from a forward simulation of 100,000 individuals, rather than aggregate population averages. The benchmark and no-experience-component profiles are computed using the same simulated initial states, productivity shocks, survival draws, and asset-position draws, so differences across profiles reflect the counterfactual policy functions rather than simulation noise. The blue area corresponds to the labour-only profile obtained when the experience component is removed, while the red area shows the additional model-implied contribution of the experience component under the benchmark productivity profile.

Table 4: **Experiment Results: Removal of the 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	1,434,467	1,104,772	897,796	0%	0%	0%
Moderately Disabled	762,292	643,059	537,446	0%	0%	0%
Severely Disabled	224,135	263,345	227,119	+36.66%	+17.88%	+16.10%
University						
Non-disabled	2,147,665	1,545,143	1,236,090	0%	0%	0%
Moderately Disabled	1,694,729	1,261,185	1,010,154	0%	0%	0%
Severely Disabled	848,369	696,977	572,483	+6.66%	+5.55%	+4.48%

Notes: The first three columns report present-value lifetime labour income, net income and consumption in the benchmark calibration, disaggregated by disability status and education level. The last three columns report percentage changes relative to the benchmark when the DSP is removed. Non-disabled and moderately disabled individuals experience no change, because the model restricts DSP medical eligibility to severely disabled individuals. The exchange rate is computed using the same procedure as described in Table 3.

Figure 13: Experiment Results: Removal of the DSP



Notes: Non-disabled and moderately disabled individuals experience no change (0%) in any outcome, because the model restricts DSP medical eligibility to severely disabled individuals. Annual labour earnings are reported in 2018-2019 prices. The figures plot simulated conditional labour income profiles for severely disabled individuals from a forward simulation of 100,000 individuals, rather than aggregate population averages. The benchmark and no-DSP profiles use the same simulated initial states, productivity shocks, survival draws, and asset-position draws, so differences across profiles reflect the counterfactual policy functions rather than simulation noise. The grey and green shaded areas indicate annual labour earnings under the benchmark model with DSP and the counterfactual model without DSP, respectively.

it comes from where each group sits relative to the means test. Non-university severely disabled individuals have low enough market income that most of them receive the full DSP payment in the benchmark, so withdrawing it removes a large share of their resources and the labour-supply response is correspondingly large. University-educated severely disabled individuals earn enough that many are already partly or fully tapered out, so the withdrawal changes their budget set much less. Lifetime net income rises by 17.9% for the non-university group and 5.6% for the university group, and lifetime consumption by 16.1% and 4.5%. Note that the labour-income response is roughly twice the net-income response in both groups: much of the additional earnings is absorbed by income tax and by the withdrawal of other means-tested support. These increases should be interpreted as income and consumption effects rather than direct welfare gains, because the additional market income is partly achieved through higher labour supply, which reduces leisure, and because the removal of the DSP also eliminates an insurance mechanism.

The associated life-cycle patterns in annual labour earnings are illustrated in Figure 13. Both profiles are jagged rather than smooth because hours are chosen from a discrete menu, so the group average jumps whenever a mass of individuals switches between adjacent hours choices.

5 Conclusion

This paper shows that disability lowers lifetime earnings not only by reducing current productivity, but also by eroding the accumulated work experience that builds pay over a career. Using HILDA Survey data, we estimate a two-stage Heckman selection model that decomposes labour productivity into labour and experience efficiency by disability status and education, allowing for the possibility that people who work despite a disability are the relatively more able ones. Moderate and severe disability reduce labour efficiency by 12% and 17%, while their effects on experience efficiency diverge: they are positive on average for moderate

disability, but imply a 23% loss for severe disability, and a 32% loss for severely disabled workers without a degree. Because the experience component accounts for around a third of pay by the mid-thirties, and more for workers without a degree, these gaps compound over the life cycle rather than remaining fixed at the point of disability onset: severely disabled workers earn 61-84% less lifetime labour income than comparable non-disabled workers and consume only 25-46% as much, and this loss is largest for non-university workers, whose earnings depend most on experience rather than formal qualifications.

Embedding these estimates in a life-cycle model of Australia’s tax-and-transfer system, including the Disability Support Pension (DSP), the Age Pension, and progressive taxation, we use two counterfactuals to trace the sources of these losses. If work experience contributed nothing to pay, lifetime earnings would fall by 23-33% across groups, and by more for every non-university group than for any university group, confirming that sustained employment history, not only current productivity, drives lifetime earnings. Removing the DSP instead raises severely disabled workers’ lifetime labour earnings by 37% among non-university workers and 7% among university graduates. This incentive effect, however, does not appear to be separable from the pension’s insurance value: both are largest for the same group, non-university workers, whose productivity loss is largest and most permanent, suggesting that the efficiency cost of income support and its insurance value are jointly determined rather than opposing forces that policymakers can trade off independently.

Because disability is modelled as a fixed trait rather than a risk realised over the life cycle, these results should be interpreted as speaking to the redistributive and incentive effects of the DSP among those already disabled, rather than to its ex-ante insurance value against the risk of becoming disabled. The model also abstracts from endogenous disability onset, dynamic selection into DSP receipt, and general-equilibrium wage effects when the DSP is removed; relaxing these assumptions is a natural direction for future work, and could clarify whether the jointness between insurance value and incentive cost documented here persists once these margins are taken into account.

These results suggest that the design of disability income support should account for the compounding, experience-driven nature of disability-related productivity loss, rather than treating recipients as a homogeneous group with a fixed earnings capacity. Because the same workers for whom the DSP provides the greatest insurance value are also those whose earnings respond most to its withdrawal, uniform eligibility and benefit rules may be a blunt instrument: policies that combine income replacement with measures preserving employment attachment and experience accumulation, such as return-to-work support or phased work requirements, could reduce the efficiency cost of income support without sacrificing its insurance function.

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A Empirical analysis

A.1 Data scope and concepts

The empirical analysis draws upon data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a nationally representative longitudinal study tracking Australian households and individuals annually since 2000-2001. The analysis uses waves 1 to 24 (covering 2000-2001 to 2023-2024). Each wave corresponds broadly to the financial year of interview (e.g., wave 1 = 2000-2001, wave 2 = 2001-2002, ..., wave 24 = 2023-2024). Wave 1 is excluded from the estimation sample due to the unavailability of the instrument. Wave 2 is excluded in the second stage equation to accommodate the one-period lagged instrumental variable used for identification in the Heckman selection model. The sample is restricted to individuals aged between 18 and 64 years. Table A.1 presents the sample sizes by age group, disability status, and education level in the pooled estimation sample. This breakdown confirms sufficient cell sizes for reliable subgroup analysis in subsequent estimations.

The primary variables used in the estimation of Equation 4 include a comprehensive set of demographic, socioeconomic, and employment-related factors. These include age, gender, marital status, employment status, state, Aboriginal and Torres Strait Islander status, disability status, education, years of schooling, and work experience. Work experience is defined as the total cumulative years an individual has spent in paid employment.

Several of these variables are directly available in the HILDA Survey dataset in pre-coded or derived form. They comprise age, gender, state of residence, Aboriginal and Torres Strait Islander status, and cumulative work experience derived from employment history calendars. The remaining variables, including marital status, employment status, disability status, highest educational attainment, and years of schooling are constructed or recoded based on responses in the survey to suit the analytical requirements of this study.

Table A.1: Sample Size by Age, Disability and Education

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

Notes: We report sample sizes by age, disability and education to confirm sufficient observations for reliable wage estimation.

Table A.2 presents a summary of the key self-constructed variables used in the analysis, including their definitions, corresponding variable labels or source variables from the HILDA Survey, measurement types, and classifications.

Married cohorts are defined as individuals who are either legally married or in a de facto relationship. All other relationship statuses are categorised as non-married. Employment status is divided into two groups: the employed and the non-employed, with the latter encompassing the unemployed and individuals not participat-

ing in the labour force. Education is defined as a binary variable distinguishing two cohorts of the Australian population based on their highest level of educational attainment. The non-university cohort comprises individuals whose highest qualification is an advanced diploma, diploma, certificate III/IV, certificate I/II, or year 12 (or below) completion without post-school qualifications. The university cohort comprises those who have completed a Bachelor degree or higher (including honours, graduate certificate/diploma, master's, or doctorate). Years of schooling is a continuous variable constructed as $ys_i = \min\{\max\{j_i - s_i - 6, 0\}, 12\}$, where ys_i , j_i and s_i denote years of schooling for individual i , age and years since full-time education, respectively. The formula assumes formal schooling begins around age 6 (primary school entry in Australia) and caps the value at 12 years to reflect a standard maximum for completed secondary education (year 12 equivalent). Constraints ensure ys_i remains bounded in the interval $[0, 12]$, preventing implausible negative or excessive values.

Table A.2: **Self-constructed Variables: Types and Classifications**

Variable Name	Label in HILDA	Type	Classification
Marital Status	Marital status from person questionnaire	Binary	<i>Married</i> : Legally married, de facto
			<i>Non-married</i> : Separated, widowed, divorced, neither married nor de facto
Employment Status	Current labour force status - broad	Binary	<i>Employed</i> : Employed
			<i>Non-employed</i> : Unemployed, not in the labour force
Disability Status	K2 Long term health condition, K3 Whether condition limits type or amount of work, K4 How much condition limits the amount of work you can do	Categorical	<i>Non-disabled</i> : No long-term condition, or a condition that does not limit work, or a limitation indicator of 0
			<i>Moderately disabled</i> : Condition limits work, with a limitation indicator between 1-5
			<i>Severely disabled</i> : Condition limits work, with a limitation indicator between 6-10, or the respondent cannot work at all
Education	DV: Highest education level achieved	Binary	<i>Non-university</i> : Year 12 or below, advanced diploma, diploma, certificate III or IV
			<i>University</i> : Bachelor, honours, graduate diploma, graduate certificate, postgraduate
Years of Schooling	DV: Time since FT education-years, DV: Age last birthday at June 30	Numerical	- - -

Disability status is a categorical variable with three levels: non-disabled, moderately disabled, and severely disabled. It is built from three questions in the HILDA person questionnaire, which are asked in sequence. The first asks whether the respondent has any long-term health condition, impairment or disability that restricts them in their everyday activities and has lasted, or is likely to last, for six months or more. Respondents who answer yes are then asked whether their conditions limit the type or amount of work they can do, with three possible answers: that they do limit work, that they have no such impact, or that the respondent cannot work at all because of them. Only respondents who give the first of those three answers are asked the final

question, which places the extent of the limitation on a scale from 0 to 10, where 0 means "not at all" and 10 means "unable to do any work". This routing matters for the coding, because it means the 0-10 score is missing by design for most respondents who report a condition, not missing at random.

The three categories follow from that sequence. A respondent is coded non-disabled if they report no long-term condition, if they report one but say it does not limit the type or amount of work they can do, or if they report one that limits work but place the limitation at 0 on the scale. These three routes carry the same economic content for our purposes: the respondent reports no work limitation. A respondent is coded moderately disabled if the condition limits work and the limitation is 1 to 5, and severely disabled if it is 6 to 10. Respondents who say they cannot work at all are also coded severely disabled. They are never asked the 0-10 question, so this is a judgement rather than a reading of the data, but "cannot work at all" is a stronger statement of work limitation than any score on the scale, and the alternative, dropping them, would remove from the analysis the group whose work capacity is most clearly impaired. The remaining case is a respondent who reports a condition but does not answer the question about whether it limits work. Their severity is unknown, so they are coded as missing rather than assigned to any group; placing them with the non-disabled would put people who report a condition into the comparison group.

The counts are as follows, over the 356,842 person-wave observations in waves 2 to 24 before the age restriction. A long-term condition is reported in 101,864 observations, or 28.5 per cent. Of those, 31,167 (30.6 per cent) report that the condition does not limit their work and 4,933 (4.8 per cent) report that they cannot work at all. The remaining 65,540 were asked the 0-10 question: 640 answered 0, 33,984 answered 1 to 5, 30,764 answered 6 to 10, and 152 gave another non-response code. A further 224 respondents with a condition did not answer the question about whether it limits work. The resulting classification is 286,657 non-disabled observations (80.3 per cent), 33,984 moderately disabled (9.5 per cent), 35,697 severely disabled (10.0 per cent), and 504 that cannot be classified (0.14 per cent). The unclassifiable share is small enough that the treatment of those observations does not affect any result in the paper. It is worth noting how much the routing matters: had the 0-10 question been treated as missing at random, the 36,100 respondents who report a condition without a score, most of whom in fact say it does not limit their work, would have been dropped or misclassified, which is a tenth of the sample rather than a rounding error.

A.2 Consumer price index

Monetary variables are adjusted for inflation using the consumer price index (CPI) to express them in real terms. Table A.3 reports the annual CPI values for the 24-financial-year panel, alongside the self-constructed price indices used for deflation. The annual CPI for each financial year is computed as the simple average of the four quarterly All Groups CPI indices, the weighted average of eight capital cities published by the Australian Bureau of Statistics (ABS), which are publicly available from the ABS website. For example, the CPI for the 2000-2001 financial year is the average of the quarterly indices for September 2000, December 2000, March 2001, and June 2001. Price indices are then computed by normalising the annual CPI series to a base period of the 2018-2019 financial year, selected as it precedes the onset of the COVID-19 pandemic and associated economic disruptions. Real values are obtained by dividing each nominal monetary variable by the corresponding year's price index.

Table A.3: CPI and Price Indices in Australia

Financial Year	Wave	CPI	Price index	Financial Year	Wave	CPI	Price index
2000-2001	1	51.0950	0.6447	2012-2013	13	71.0125	0.8961
2001-2002	2	52.5600	0.6632	2013-2014	14	72.9475	0.9205
2002-2003	3	54.1800	0.6837	2014-2015	15	74.1875	0.9361
2003-2004	4	55.4575	0.6998	2015-2016	16	75.2050	0.9490
2004-2005	5	56.7975	0.7167	2016-2017	17	76.4925	0.9652
2005-2006	6	58.6275	0.7398	2017-2018	18	77.9800	0.9840
2006-2007	7	60.3375	0.7614	2018-2019	19	79.2500	1.0000
2007-2008	8	62.3900	0.7873	2019-2020	20	80.3225	1.0135
2008-2009	9	64.3275	0.8117	2020-2021	21	81.6025	1.0297
2009-2010	10	65.8275	0.8306	2021-2022	22	85.2600	1.0758
2010-2011	11	67.8725	0.8564	2022-2023	23	91.2500	1.1514
2011-2012	12	69.4500	0.8763	2023-2024	24	95.0725	1.1997

Source: Consumer Price Index, Australia. ABS.

Notes: The price indices are indexed to 2018-2019 rate.

A.3 Descriptive analysis

Table A.4 provides descriptive statistics for the key variables in the estimation sample, disaggregated by age group. Individuals aged 28-57 account for about 65% of the HILDA sample. A higher prevalence of disability and reported work limitations is observed among the older population. Labour market outcomes display a typical life-cycle pattern: employment rates and average annual working hours increase gradually during early adulthood, peak in mid-career, and then decline in later years.

Table A.5 reports additional summary statistics, stratified by disability status and educational attainment. Relative to their non-disabled counterparts, individuals with disability tend to be older, less likely to be married or in a de facto relationship, less educated, and substantially more likely to be non-employed. Likewise, individuals in the non-university education category show a higher prevalence of disability and are more likely to be non-married compared with those who have attained university-level qualifications.

Although individuals with disability exhibit a higher probability of non-employment, they accumulate more years of employment on average than their non-disabled counterparts. This counterintuitive pattern is largely attributable to differences in age distribution: individuals with moderate or severe disabilities tend to be older on average, thereby having had more time to accrue work experience prior to any onset or worsening of disability.

Figure A.1 illustrates the distribution of cumulative work experience, stratified by disability status and educational attainment. The histograms show that, conditional on age, individuals with disability, whether moderate or severe, generally have lower work experience than non-disabled individuals. This pattern holds across both the non-university and university-educated subgroups. The distributions for non-disabled groups are denser, with higher and more pronounced peaks, reflecting more consistent and substantial accumulation of employment years. In contrast, the distributions for disabled groups are sparser, with lower peaks and greater spread, suggesting greater variability and reduced overall experience, likely stemming from employment barriers, health-related interruptions, or reduced labour force attachment over the life cycle.

Thus, while the older average age among individuals with disabilities contributes to a higher unconditional

Table A.4: 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)

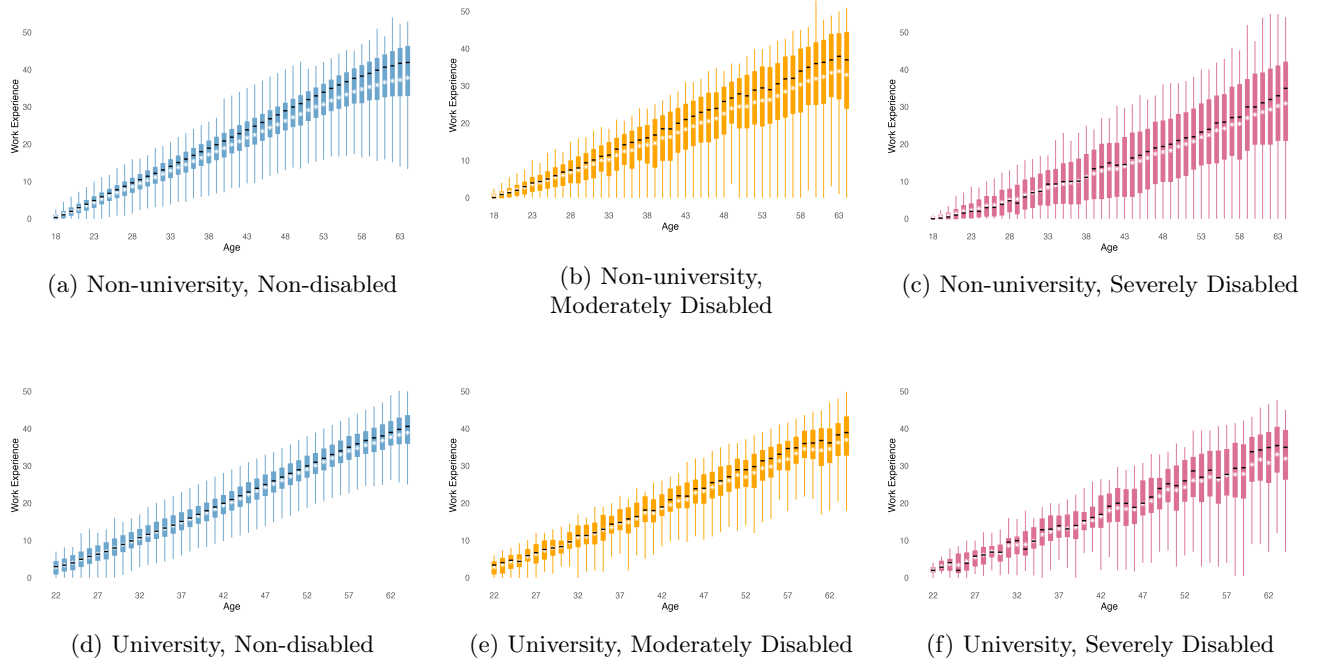
Notes: The first row shows the percentage of each age group in the sample. The variables *male*, *married*, *university*, *employed* and *disabled* are reported as weighted percentages, reflecting the proportion of individuals in each category. All other variables are presented as weighted means. The variable *disabled* captures individuals with moderate or severe disabilities, *work experience* represents the number of years employed, and *working hours* is expressed as the annual total number of hours worked. Regarding the variable *limitation score*, it captures the response to the question, "K4: To what extent does your condition limit the amount of work you can do?" with responses ranging from 0 ("not at all") to 10 ("unable to do any work"). The score is set to zero for everyone recorded as non-disabled, including those who report a condition that does not limit their work, so the mean is taken over the whole age group rather than over the disabled alone. Respondents who report being unable to work at all are never asked the question and are scored at 10. Standard deviations are provided in parentheses alongside each estimate.

Table A.5: Summary Statistics by Disability and Education

<i>Variable</i>	<i>Disability</i>			<i>Education</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)

Notes: The variables *male*, *married*, *university*, *employed* and *disabled* are reported as weighted percentages, reflecting the proportion of individuals in each category. All other variables are presented as weighted means. The variable *limitation score* is unavailable within the non-disabled cohorts as they do not face any work restrictions. Standard deviations are provided in parentheses alongside each estimate.

Figure A.1: Distribution of Work Experience By Disability Status and Education



Notes: The box plots in each panel display the 25th and 75th percentiles, with white stars indicating the median and black lines representing the mean. Vertical lines depict data points within the 95th percentile of the distribution.

mean of work experience, the conditional (age-adjusted) distributions reveal distinct life-cycle trajectories characterised by greater challenges in sustained employment accumulation among those with disability.

A.4 Estimation of labour productivity

Instrumental relevance and validity. A key challenge in estimating wage equations is that wages are observed only for individuals who are employed, which introduces selection bias into the sample. This issue is particularly pronounced among individuals with disabilities, where non-employment rates are substantially higher, potentially leading to non-random selection into the labour market and biased estimates of wage determinants for the broader population. To address this selection problem, we employ the two-step correction procedure developed by Heckman (1979), which requires a valid exclusion restriction: a variable that is strongly associated with the probability of employment but has no direct effect on wages conditional on employment and other covariates.

Recent studies, such as Low and Pistaferri (2015) and Kim and Rhee (2022), have constructed potential tax-and-transfer variables to serve as exclusion restrictions in Heckman selection models. However, we find this approach unsuitable for the HILDA dataset. Due to the progressive structure of Australian taxation and the widespread use of means-tested benefits, such constructed variables are inherently correlated with real earnings, thereby violating the exogeneity requirement of the exclusion restriction.

We initially use weekly time spent on household errands as a potential exclusion restriction⁵. Household

⁵Note that household errands differ from housework in the HILDA Survey. Housework includes preparing meals, washing

errands refer to activities such as shopping, banking, paying bills, and keeping financial records. This measure captures non-market time commitments that are closely related to household organisation, domestic responsibility, and the opportunity cost of market work. Individuals who spend more time on errands may face greater constraints on their availability for paid employment, or may be more likely to specialise in non-market household production. For this reason, household errands are plausibly relevant for employment selection. At the same time, conditional on demographic characteristics, education, disability status, household composition, and other controls, time spent on errands is less likely to directly affect offered wages than variables more closely related to productivity, occupation, or labour market skills.

However, the contemporaneous measure is problematic due to reverse causality. Employment decisions, and particularly hours worked among the employed, directly reduce the time available for household errands. As a result, current errands may be endogenous to unobservables, such as health-related constraints, preferences for home production, or household bargaining arrangements, that jointly influence current wages, employment probability, and time allocation to non-market activities. To mitigate this concern, we use the one-year lagged value of time spent on household errands as the main exclusion restriction. Lagging the instrument reduces contemporaneous reverse causality by using past household routines to predict current employment selection. The identifying assumption is that, after conditioning on the included covariates, lagged errands affect current wages only through their effect on employment selection, rather than through a direct productivity or wage channel. Under this assumption, lagged household errands capture predetermined non-market time commitments that influence the decision to work, while remaining excluded from the wage equation.

The exclusion restriction is plausible because lagged household errands are unlikely to exert a direct effect on current wages. Empirical evidence from the housework-wage literature supports this claim. For example, [Noonan \(2001\)](#) categorises tasks traditionally shared between men and women as "neutral" tasks, including shopping, paying bills, and driving other household members. The results show no significant relationship between these tasks and hourly wages after conditioning on observables. Similarly, [Hersch and Stratton \(2002\)](#) document that the "neutral" category of housework, which includes paying bills and driving others, has no significant effect on wages for either women or men, while significantly negative effects are concentrated in routine female-typed tasks. Related evidence ([Bonke, Datta Gupta and Smith \(2004\)](#), [Bryan and Sevilla-Sanz \(2011\)](#)) also suggests that wage penalties from household production are not uniform across tasks. Studies that distinguish the timing, flexibility, or type of domestic work generally find that wage effects are more closely associated with routine, inflexible, or traditionally female-typed tasks, rather than with more flexible household-management activities. Together, these studies suggest that household errands are less likely to have a direct effect on wages once employment status and observed covariates are controlled for, supporting the validity of the lagged measure as an exclusion restriction in this context.

Table [A.6](#) reports diagnostic tests of instrument relevance and validity for the Heckman selection model. In the baseline specification, the exclusion restriction is the one-year lagged time spent on household errands. The relevance test rejects the null that lagged errands have no explanatory power in the employment equation, with a Wald statistic of 53.9 on one degree of freedom. In the second specification, contemporaneous time spent on household errands is added alongside the lagged measure, and the joint statistic rises to 72.8 on two degrees of freedom. Both instruments are therefore relevant for employment selection.

To assess the exclusion restriction we add the instruments to the second-stage wage equation and test their joint significance. The null is that they have no direct effect on wages once employment and the included dishes and clothes, cleaning house, ironing and sewing.

Table A.6: **Relevance and Validity: Instrumental Variable in First-stage**

	<i>(i) Relevance</i>		<i>(ii) Validity</i>	
χ^2	53.90***	72.80***	0.02	2.40
p-value	0.0000	0.0000	0.8757	0.3017
Lagged Household Errands	✓	✓	✓	✓
Current Household Errands		✓		✓
Sample Size	93,374	93,374	93,374	93,374

Notes: Relevance is assessed with a Wald test of the null that the excluded instrument, or instruments, have no explanatory power in the employment probit. Validity is assessed with a Wald test of the null that the instruments have no direct effect on wages, obtained by adding them to the second-stage equation and testing their joint significance. Both tests use the same sample, which is the set of observations for which the instruments, the wage and all covariates are observed, so relevance and validity are judged on identical data. Reported p-values are based on the corresponding asymptotic distributions. We also re-estimated both stages using weekly time spent on outdoor tasks as the excluded variable instead of errands, on the sample for which both instruments are observed, and report the comparison in the replication output.

covariates are conditioned on. In the baseline specification the test statistic is 0.02 with a p-value of 0.88, so the null is not rejected; adding current errands alongside the lagged measure gives 2.40 with a p-value of 0.30, which again does not reject. Both tests use the same sample as the corresponding relevance test. Taken together, lagged household errands predict selection into employment and show no detectable direct association with wages once the model controls are included. Two caveats belong with that conclusion. A failure to reject is not proof of validity, particularly with a test of this power; and time spent on household errands could in principle be correlated with unobserved determinants of wages, such as household bargaining or the division of domestic labour, in ways this test would not detect. We treat the exclusion restriction as plausible rather than established, which is also why Table A.9 reports the estimates with and without the selection correction side by side.

The choice of exclusion restriction deserves to be shown rather than asserted, because a time-use variable that predicts employment is easy to find and one that plausibly does not affect wages directly is not. Table A.7 reports all nine candidates we examined, with the same two tests applied to each. Four fail on relevance or come close to it. Housework has a weak association with employment, care of other children and care of an adult have none, and none of the three would identify the selection equation. Four others fail on exclusion. Housework, child care and volunteering all show a direct association with wages that rejects at the one per cent level, which is what one would expect if they proxy for household circumstances that also affect pay. Errands lagged two waves fails at the ten per cent level. Three candidates pass both: errands lagged one wave, errands in the current wave, and outdoor tasks lagged one wave. We use errands lagged one wave. The lag is what makes the restriction defensible, since a contemporaneous time-use measure is chosen jointly with hours of work, and errands is the strongest of the lagged candidates on relevance. Outdoor tasks would serve as an alternative, and the main estimates are similar when it is used instead.

First stage and second stage results. Table A.8 presents the full results of the first-stage selection equation, which includes the lagged household-errand variable as the exclusion restriction along with other covariates. The inverse Mills ratio derived from this regression is then included in the second-stage wage equation to correct for selection bias.

Table A.9 reports the estimated coefficients from the second-stage wage equations. The left column

Table A.7: Candidate Exclusion Restrictions

Candidate	Relevance: Wald	Relevance: partial F	Exclusion: Wald	Exclusion: p-value	Usable
Errands, lagged one wave	53.90***	46.61	0.02	0.8757	yes
Errands, lagged two waves	39.59***	34.64	2.95	0.0857	no
Errands, current wave	72.14***	61.54	1.46	0.2263	yes
Outdoor tasks, lagged	28.50***	25.89	1.52	0.2177	yes
Housework, lagged	5.79*	5.25	18.02***	0.0000	no
Child care, lagged	36.68***	33.65	13.93***	0.0002	no
Care of other children, lagged	3.77	4.69	5.14*	0.0234	no
Volunteering, lagged	15.48***	13.28	14.52***	0.0001	no
Care of an adult, lagged	0.12	0.19	2.07	0.1502	no

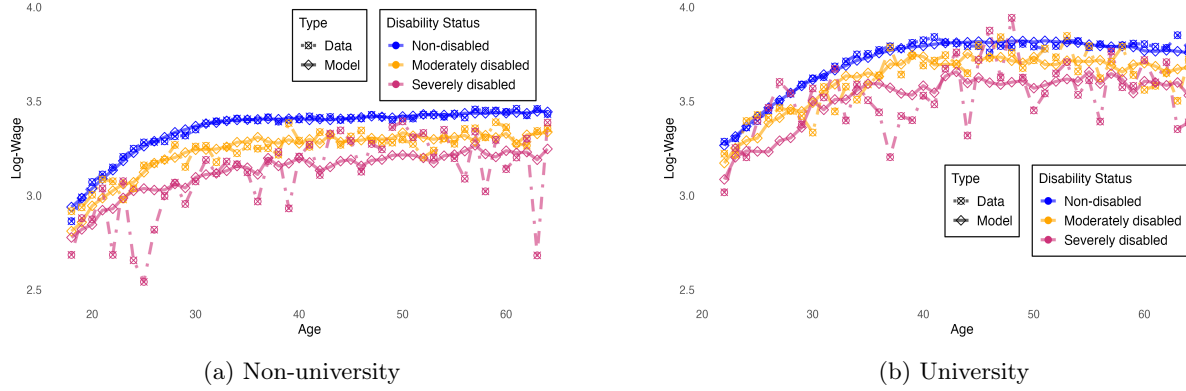
Notes: Each row tests one time-use variable as a candidate exclusion restriction. Relevance is the Wald statistic on the candidate in the employment probit, with the partial F from the corresponding linear probability model alongside it. Exclusion is the Wald statistic on the candidate when it is added to the second-stage wage equation. A candidate is marked usable if it is relevant at the one per cent level and its exclusion test does not reject at the ten per cent level. Significance stars refer to the test statistic in the same column.

Table A.8: First-stage Probit Regression Results

Variable	Coefficient		Variable	Coefficient	
Moderately Disabled	-0.3340***	(0.0177)	A/TS Islander Status	-0.1134**	(0.0382)
Severely Disabled	-0.9718***	(0.0232)	State		
Age	-0.0661***	(0.0031)	VIC	-0.0742***	(0.0182)
Age ²	0.0000	(0.0001)	QLD	-0.0518**	(0.0194)
Experience	0.1630***	(0.0048)	SA	-0.0094	(0.0277)
Experience ²	-0.0035***	(0.0002)	WA	-0.0033	(0.0272)
Experience ³	0.0000***	(0.0000)	TAS	0.1354***	(0.0383)
Married	-0.0925***	(0.0144)	NT	0.0105	(0.0660)
Male	-0.0188	(0.0138)	ACT	0.0487	(0.0419)
University	0.2507***	(0.0161)	Lagged Household Errands	-0.0228***	(0.0012)
Sample Size	168,515				
Pseudo R^2	0.1414				

Notes: Financial-year dummies are included in the regression. Standard errors are clustered and reported in parentheses. Significance levels are denoted as follows: ***p < 0.001, **p < 0.01, *p < 0.05.

Figure A.2: Data VS Model: Life-cycle Log-Wage Trends



Notes: Non-university individuals enter the labour market at age 18, while university graduates enter at age 22. Log wages are indexed to the 2018-2019 rate as the base year.

shows results from the Heckman-corrected model and the right column the uncorrected estimates. Both are estimated on the same 108,702 observations, so the two columns differ only by the inclusion of the inverse Mills ratio and not by a change of sample. The uncorrected labour-efficiency penalties are smaller in every cell. For moderately disabled non-university individuals the penalty is 11.50% without the correction against 13.60% with it, and for severely disabled non-university individuals 11.17% against 16.94%. Among university-educated individuals the corresponding figures are 8.31% against 11.05% for moderate disability and 12.69% against 17.65% for severe disability. The direction is what selection on unobservables would produce: if the disabled people who work are the more able ones, ignoring that understates the penalty. The magnitude should not be over-read, however. The selection term itself is not statistically significant, so the differences between the two columns, while consistent in sign across all four cells, are not individually distinguishable from sampling variation. The useful conclusion is the narrower one: the estimated disability penalties are not an artefact of the selection correction, since they survive its removal with the same ordering and similar magnitudes.

Model fit and robustness analysis. Although the benchmark regression model effectively captures average wage patterns across the sample, it is less successful in explaining the substantial heterogeneity in earnings among individuals with severe disabilities. Figure A.2 illustrates this limitation by presenting age profiles of log real wages for non-university and university-educated cohorts, stratified by disability status. The profiles highlight considerable dispersion in wage trajectories among severely disabled individuals, indicating that the baseline model may not fully accommodate the underlying heterogeneity in returns to observables or unobservables.

To assess the robustness of these findings, we estimate a series of alternative specifications following Kim and Rhee (2022). Table A.10 presents the results. Column (1) reports the benchmark specification, in which the labour efficiency component (λ_L) and experience efficiency component (λ_E) are permitted to vary by education level, while the non-linear experience function $g(e)$ is assumed to be common across education groups. The other three columns relax or tighten that structure in turn. Column (2) lets the cumulative experience function vary by education as well, so that every component of the wage equation is education-

Table A.9: Second-stage Non-linear regression Results: With or Without Selection Control

Coefficients		(1) With Selection Control	(2) Without Selection Control
Labour			
<i>Non-university</i>	$\lambda_{L,1}$	0.0068 (0.0047)	0.0095** (0.0032)
	$\lambda_{L,2}$	0.0000 (0.0001)	-0.0000 (0.0001)
<i>University</i>	$\lambda_{L,0}$	0.1878*** (0.0325)	0.1861*** (0.0306)
	$\lambda_{L,1}$	0.0205*** (0.0051)	0.0216*** (0.0043)
	$\lambda_{L,2}$	-0.0002 (0.0001)	-0.0002* (0.0001)
Experience			
<i>Non-university</i>	$\lambda_{E,1}$	-0.0473* (0.0220)	-0.0482* (0.0238)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0011* (0.0005)
<i>University</i>	$\lambda_{E,0}$	-0.6023** (0.2082)	-0.8012*** (0.2262)
	$\lambda_{E,1}$	0.0266 (0.0258)	0.0467 (0.0284)
	$\lambda_{E,2}$	-0.0024*** (0.0006)	-0.0030*** (0.0007)
Inverse Mills Ratio		0.0800 (0.0544)	- - -
Disability			
<i>Non-university</i>	$\ln \phi_L(MD, LE)$	-0.1462** (0.0452)	-0.1222*** (0.0362)
	$\ln \phi_L(SD, LE)$	-0.1856* (0.0734)	-0.1185 (0.0635)
<i>University</i>	$\ln \phi_L(MD, HE)$	-0.1171 (0.0599)	-0.0868 (0.0504)
	$\ln \phi_L(SD, HE)$	-0.1942* (0.0910)	-0.1357 (0.0716)
Accumulated Experience			
γ_1		0.0477 (0.0494)	0.0608 (0.0606)
γ_2		-0.0028 (0.0026)	-0.0042 (0.0035)
γ_3		0.0001 (0.0001)	0.0001 (0.0001)
Relative Efficiency of E to L			
<i>Non-university</i>	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2146*** (0.1518)	1.2062*** (0.1649)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8231** (0.2537)	0.6963* (0.2769)
<i>University</i>	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1924*** (0.2811)	1.1239*** (0.2802)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0510** (0.3997)	0.9807* (0.4064)
Sample Size		108,702	108,702
Weighted R^2		0.2706	0.2704

Notes: The second-stage equation controls for state-specific linear time trends and wave-specific dummies for marital status, years of schooling and gender. Individual sample weights are used. Clustered standard errors are denoted in parentheses. Significance levels are given as follows: ***p<0.001, **p<0.01, *p<0.05.

Table A.10: Robustness Check: Alternative Specifications

Coefficients		(1) Benchmark	(2)	(3)	(4)
Labour					
<i>Non-university</i>	$\lambda_{L,1}$	0.0068 (0.0047)	0.0114** (0.0040)	0.0068 (0.0047)	0.0058 (0.0051)
	$\lambda_{L,2}$	0.0000 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
<i>University</i>	$\lambda_{L,0}$	0.1878*** (0.0325)	0.2253*** (0.0380)	0.1875*** (0.0325)	0.3006*** (0.0111)
	$\lambda_{L,1}$	0.0205*** (0.0051)	0.0050 (0.0080)	0.0207*** (0.0050)	- - -
	$\lambda_{L,2}$	-0.0002 (0.0001)	0.0001 (0.0002)	-0.0002* (0.0001)	- - -
Experience					
<i>Non-university</i>	$\lambda_{E,1}$	-0.0473* (0.0220)	-0.1052*** (0.0319)	-0.0471* (0.0222)	-0.0347 (0.0232)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0002 (0.0006)	-0.0010* (0.0004)	-0.0008 (0.0005)
<i>University</i>	$\lambda_{E,0}$	-0.6023** (0.2082)	-0.1948 (0.3356)	-0.5977** (0.2094)	- - -
	$\lambda_{E,1}$	0.0266 (0.0258)	0.0694** (0.0245)	0.0260 (0.0258)	- - -
	$\lambda_{E,2}$	-0.0024*** (0.0006)	-0.0023*** (0.0005)	-0.0024*** (0.0006)	- - -
Inverse Mills Ratio		0.0800 (0.0544)	0.0850 (0.0532)	0.0769 (0.0540)	0.0916 (0.0556)
Disability					
<i>Non-university</i>	$\ln \phi_L(MD, LE)$	-0.1462** (0.0452)	-0.1487*** (0.0433)	-0.1333*** (0.0376)	-0.1326** (0.0445)
	$\ln \phi_L(SD, LE)$	-0.1856* (0.0734)	-0.1932** (0.0678)	-0.1782** (0.0625)	-0.2054* (0.0829)
<i>University</i>	$\ln \phi_L(MD, HE)$	-0.1171 (0.0599)	-0.1266 (0.0759)	- - -	-0.1747* (0.0840)
	$\ln \phi_L(SD, HE)$	-0.1942* (0.0910)	-0.1091 (0.1104)	- - -	-0.1742 (0.1168)
Accumulated Experience					
<i>Non-university</i>	$\gamma_1(LE)$	0.0477 (0.0494)	0.1861 (0.1418)	0.0488 (0.0503)	0.0472 (0.0456)
	$\gamma_2(LE)$	-0.0028 (0.0026)	-0.0075 (0.0074)	-0.0029 (0.0027)	-0.0017 (0.0016)
	$\gamma_3(LE)$	0.0001 (0.0001)	0.0003 (0.0003)	0.0001 (0.0001)	0.0000 (0.0000)
<i>University</i>	$\gamma_1(HE)$	- - -	-0.0061 (0.0327)	- - -	- - -
	$\gamma_2(HE)$	- - -	-0.0010 (0.0016)	- - -	- - -
	$\gamma_3(HE)$	- - -	0.0000 (0.0000)	- - -	- - -
Relative Efficiency of E to L					
<i>Non-university</i>	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2146*** (0.1518)	1.2555*** (0.1605)	1.1888*** (0.1291)	1.1128*** (0.1426)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8231** (0.2537)	0.8255** (0.2603)	0.8307*** (0.2212)	0.8722*** (0.2642)
<i>University</i>	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1924*** (0.2811)	1.1599*** (0.2448)	- - -	1.4404*** (0.3490)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0510** (0.3997)	0.7556* (0.3151)	- - -	1.0099* (0.4209)
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		0.2706	0.2713	0.2705	0.2666

Notes: This robustness check tests the benchmark model by allowing the labour efficiency component (λ_L), experience efficiency component (λ_E), disability terms, (ϕ_L and ϕ_E), and accumulated experience function ($g(e)$), to vary by education level or remain education-independent. The benchmark model restricts education dependence to only the efficiency components and disability terms.

specific. Column (3) instead pools the disability terms across education, imposing a single moderate and a single severe effect. Column (4) pools the efficiency profiles across education while keeping the disability terms education-specific. The disability penalties are stable across all four. The moderate non-university penalty ranges from -0.133 to -0.149 in log points and the severe non-university penalty from -0.173 to -0.205, against benchmark values of -0.146 and -0.186, and the relative-efficiency parameters stay within a similar band. The specification choice therefore does not drive the paper’s estimates. Two features of the table are worth noting for what they say about precision rather than robustness. In column (2) the education-specific experience polynomials are estimated very imprecisely, with a positive first coefficient for non-university workers and a negative one for university graduates but neither statistically distinguishable from zero, which is why the benchmark keeps a single polynomial. In column (3), pooling the disability terms tightens their standard errors, as it must, but it also forces the moderate and severe effects to be identical across education groups, which the benchmark estimates in Table 2 suggest is a poor approximation for the severe state, where the non-university and university effects on experience efficiency differ by a factor of two.

Tables A.11 and A.12 provide further robustness checks, the first by varying how the standard errors are computed and the second by adding year-specific control variables. Two things are worth drawing out of Table A.11. First, the choice of variance estimator matters for how significant the estimates look. The robust standard errors that ignore the panel structure are the smallest in every row, and under them most parameters are significant, including the inverse Mills ratio. Clustering on the person raises them substantially, which is the expected consequence of repeated observations on the same individuals, and the bootstrap standard errors are larger again for most parameters. We report the person-clustered errors in the main tables, which is the middle of the three, and the bootstrap errors alongside them where they are available. Second, the parameters that carry the paper’s conclusions survive the most conservative treatment. The labour-efficiency penalty for moderately disabled non-university workers remains significant under the bootstrap, as do three of the four relative-efficiency parameters. The two severe-disability labour-efficiency penalties, the relative-efficiency parameter for severely disabled non-university workers, and the experience-efficiency age terms do not. That is worth stating plainly rather than resting on the clustered errors alone: the qualitative pattern of the estimates is robust, but the precision of the severe-disability parameters is limited by how few severely disabled people are observed in employment.

A.5 Sample selection

Table A.13 records every restriction that takes the data from the raw HILDA release to the samples used in the paper, so that each reported sample size can be traced to the restrictions that produce it. Two features are worth drawing out. First, the first-stage probit and the second-stage wage equation are estimated on different samples by construction, not by choice: the wage equation can only use people with an observed positive wage, which excludes the non-employed, and the selection correction is the device that addresses exactly that. Second, the binding restriction on the second-stage sample is neither the wage nor the hours requirement but the availability of the lagged instrument. Requiring a time-use response in the previous wave removes about a third of the person-years that would otherwise be usable. That is the price of the exclusion restriction, and it is worth stating because it means the estimation sample is drawn disproportionately from individuals with longer unbroken response histories.

Table A.11: Robustness Check: Alternative Variance Estimators

Coefficients		(1) Benchmark	(2)	(3)	(4)
Labour					
Non-university	$\lambda_{L,1}$	0.0068 (0.0047)	0.0068* (0.0029)	0.0068 (0.0047)	0.0068 (0.0058)
	$\lambda_{L,2}$	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
University	$\lambda_{L,0}$	0.1878*** (0.0325)	0.1878*** (0.0254)	0.1878*** (0.0331)	0.1878** (0.0576)
	$\lambda_{L,1}$	0.0205*** (0.0051)	0.0205*** (0.0033)	0.0205*** (0.0049)	0.0205 (0.0140)
	$\lambda_{L,2}$	-0.0002 (0.0001)	-0.0002** (0.0001)	-0.0002* (0.0001)	-0.0002 (0.0004)
Experience					
Non-university	$\lambda_{E,1}$	-0.0473* (0.0220)	-0.0473*** (0.0140)	-0.0473* (0.0224)	-0.0473 (0.0627)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0010*** (0.0003)	-0.0010* (0.0004)	-0.0010 (0.0013)
University	$\lambda_{E,0}$	-0.6023** (0.2082)	-0.6023*** (0.1411)	-0.6023** (0.1975)	-0.6023 (0.3489)
	$\lambda_{E,1}$	0.0266 (0.0258)	0.0266 (0.0168)	0.0266 (0.0246)	0.0266 (0.0922)
	$\lambda_{E,2}$	-0.0024*** (0.0006)	-0.0024*** (0.0004)	-0.0024*** (0.0006)	-0.0024 (0.0022)
Inverse Mills Ratio		0.0800 (0.0544)	0.0800* (0.0323)	0.0800 (0.0489)	0.0800 (0.0760)
Disability					
Non-university	$\ln \phi_L(MD, LE)$	-0.1462** (0.0452)	-0.1462*** (0.0302)	-0.1462** (0.0499)	-0.1462** (0.0464)
	$\ln \phi_L(SD, LE)$	-0.1856* (0.0734)	-0.1856*** (0.0543)	-0.1856** (0.0617)	-0.1856 (0.1339)
University	$\ln \phi_L(MD, HE)$	-0.1171 (0.0599)	-0.1171** (0.0415)	-0.1171* (0.0572)	-0.1171 (0.0634)
	$\ln \phi_L(SD, HE)$	-0.1942* (0.0910)	-0.1942** (0.0692)	-0.1942* (0.0906)	-0.1942 (0.1037)
Accumulated Experience					
γ_1		0.0477 (0.0494)	0.0477 (0.0348)	0.0477 (0.0457)	0.0477 (1.2972)
γ_2		-0.0028 (0.0026)	-0.0028 (0.0018)	-0.0028 (0.0024)	-0.0028 (0.0274)
γ_3		0.0001 (0.0001)	0.0001* (0.0000)	0.0001 (0.0001)	0.0001 (0.0006)
Relative Efficiency of E to L					
Non-university	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2146*** (0.1518)	1.2146*** (0.1145)	1.2146*** (0.1688)	1.2146*** (0.1737)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8231** (0.2537)	0.8231*** (0.1936)	0.8231*** (0.2163)	0.8231 (0.6603)
University	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1924*** (0.2811)	1.1924*** (0.1941)	1.1924*** (0.2665)	1.1924*** (0.3385)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0510** (0.3997)	1.0510*** (0.3116)	1.0510** (0.4011)	1.0510* (0.4575)
Variance estimator					
Person clustering		✓		✓	
Wave clustering				✓	
Bootstrap resampling					✓
Sample Size		108,702	108,702	108,702	108,702
Weighted R^2		0.2706	0.2706	0.2706	0.2706

Notes: All four columns report the same point estimates and differ only in how the standard errors are computed. Column (1) is the benchmark, which clusters at the person level. Column (2) is heteroskedasticity-robust with no clustering. Column (3) clusters two-way on person and wave. Column (4) reports two-step bootstrap standard errors from 199 person-level resamples of the full estimation chain, probit and wage equation together, with significance stars recomputed from the bootstrap ratio. Clustering on waves alone or states alone is not reported. A cluster-robust variance matrix has rank at most the number of clusters, so with 146 parameters and only 22 waves or 8 states the resulting standard errors would be mechanically too small rather than informatively different.

Table A.12: Robustness Check: Additional Year-specific Control Variables

Coefficients		(1) Benchmark	(2)	(3)	(4)
Labour					
<i>Non-university</i>	$\lambda_{L,1}$	0.0068 (0.0047)	0.0070 (0.0046)	0.0067 (0.0048)	0.0078 (0.0044)
	$\lambda_{L,2}$	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
<i>University</i>	$\lambda_{L,0}$	0.1878*** (0.0325)	0.1884*** (0.0321)	0.1869*** (0.0326)	0.2008*** (0.0331)
	$\lambda_{L,1}$	0.0205*** (0.0051)	0.0206*** (0.0050)	0.0206*** (0.0051)	0.0204*** (0.0049)
	$\lambda_{L,2}$	-0.0002 (0.0001)	-0.0002* (0.0001)	-0.0002 (0.0001)	-0.0002 (0.0001)
Experience					
<i>Non-university</i>	$\lambda_{E,1}$	-0.0473* (0.0220)	-0.0474* (0.0223)	-0.0472* (0.0220)	-0.0494* (0.0210)
	$\lambda_{E,2}$	-0.0010* (0.0004)	-0.0010* (0.0004)	-0.0010* (0.0004)	-0.0010* (0.0004)
<i>University</i>	$\lambda_{E,0}$	-0.6023** (0.2082)	-0.6294** (0.2145)	-0.5898** (0.2066)	-0.5858** (0.2058)
	$\lambda_{E,1}$	0.0266 (0.0258)	0.0288 (0.0262)	0.0251 (0.0258)	0.0237 (0.0254)
	$\lambda_{E,2}$	-0.0024*** (0.0006)	-0.0025*** (0.0006)	-0.0024*** (0.0006)	-0.0024*** (0.0006)
Inverse Mills Ratio		0.0800 (0.0544)	0.0674 (0.0544)	0.0814 (0.0545)	0.0711 (0.0529)
Disability					
<i>Non-university</i>	$\ln \phi_L(MD, LE)$	-0.1462** (0.0452)	-0.1419** (0.0447)	-0.1467** (0.0452)	-0.1450** (0.0449)
	$\ln \phi_L(SD, LE)$	-0.1856* (0.0734)	-0.1763* (0.0724)	-0.1865* (0.0736)	-0.1733* (0.0715)
<i>University</i>	$\ln \phi_L(MD, HE)$	-0.1171 (0.0599)	-0.1127 (0.0586)	-0.1180 (0.0605)	-0.1139 (0.0592)
	$\ln \phi_L(SD, HE)$	-0.1942* (0.0910)	-0.1846* (0.0893)	-0.1953* (0.0919)	-0.1889* (0.0893)
Accumulated Experience					
γ_1		0.0477 (0.0494)	0.0496 (0.0512)	0.0474 (0.0491)	0.0489 (0.0492)
γ_2		-0.0028 (0.0026)	-0.0030 (0.0027)	-0.0028 (0.0026)	-0.0033 (0.0028)
γ_3		0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Relative Efficiency of E to L					
<i>Non-university</i>	$\phi_E(MD, LE)/\phi_L(MD, LE)$	1.2146*** (0.1518)	1.2114*** (0.1528)	1.2139*** (0.1516)	1.2260*** (0.1534)
	$\phi_E(SD, LE)/\phi_L(SD, LE)$	0.8231** (0.2537)	0.8118** (0.2555)	0.8222** (0.2533)	0.7976** (0.2515)
<i>University</i>	$\phi_E(MD, HE)/\phi_L(MD, HE)$	1.1924*** (0.2811)	1.1847*** (0.2811)	1.1947*** (0.2827)	1.1964*** (0.2825)
	$\phi_E(SD, HE)/\phi_L(SD, HE)$	1.0510** (0.3997)	1.0376** (0.4002)	1.0511** (0.4015)	1.0645** (0.4036)
Year-specific Control Variables					
Gender		✓	✓	✓	✓
Marital Status		✓	✓	✓	✓
Years of Schooling		✓	✓	✓	✓
A/TS Islander status			✓		
Remoteness				✓	
Family Structure: Dependent Children					✓
Sample Size		108,702	108,702	108,677	108,702
Weighted R^2		0.2706	0.2708	0.2709	0.2714

Notes: This robustness check compares the benchmark model with alternative models that incorporate additional year-specific explanatory variables in the second-stage equation, including binary indicators for Aboriginal and Torres Strait Islander status, remoteness, and the presence of at least one dependent child. The Aboriginal and Torres Strait Islander status variable is based on self-reported data from HILDA. The remoteness indicator is self-constructed using the "ASGC 2001 Remoteness Area" label in HILDA, categorising individuals in major cities, inner regional, or outer Regional Australia as non-remote, and those in remote or very remote Australia as remote. Similarly, the family structure variable is derived from the "Household Type" variable in HILDA, with households identified as couple families, lone-parent families, or other household types with at least one dependent child classified as having a dependent child, and those without dependent children grouped accordingly.

Table A.13: Sample Selection Ledger

Step	Person-year observations	Individuals
<i>Master sample</i>		
HILDA waves 2-24, all responding persons	356,842	35,864
Ages 18 to 64	274,967	30,954
<i>First-stage employment probit</i>		
Master sample with all probit regressors observed	168,515	
<i>Second-stage wage equation</i>		
Master sample	274,967	30,954
Waves 3-24 (one-wave lagged instrument required)	264,608	30,054
Positive usual weekly hours	203,098	25,687
Positive observed wage	166,072	24,032
Valid sample weight	165,194	23,934
All model regressors observed	108,702	15,498
<i>Productivity shock process</i>		
Two or more consecutive waves per person	103,245	

Notes: Each row applies the restriction named to the sample remaining above it. The first-stage probit and the second-stage wage equation are estimated on nested but different samples: the probit uses everyone whose employment status and covariates are observed, while the wage equation additionally requires a positive observed wage, which by construction excludes the non-employed, and requires the inverse Mills ratio, which requires a time-use response in the previous wave. The single largest restriction on the second-stage sample is the last one, which reflects the lagged-instrument requirement rather than missing wage data. Individual counts are omitted where the estimation is not person-clustered.

A.6 The idiosyncratic productivity process

The structural model needs a process for the idiosyncratic component of productivity. Rather than importing one from the literature, we estimate it from the residual of the second-stage wage equation, so that the deterministic and stochastic parts of productivity come from the same equation and the same sample. The residual has already had the estimated age, education, disability, year, location and employment-selection terms removed, so what remains is the idiosyncratic wage variation the model is meant to capture, not disability-related wage differences that the model represents separately through the efficiency profiles. We trim the extreme 0.5 per cent of each tail, which limits the influence of wage-hours ratio errors while retaining part-time workers, and we keep individuals observed in at least two consecutive waves. The estimates are reported in Table A.14. The persistence of 0.81 and the innovation standard deviation of 0.12 imply a stationary standard deviation of the persistent component of 0.20, alongside permanent heterogeneity of 0.23 and a transitory component of 0.21.

One step in this construction deserves to be reported rather than assumed. The model treats the idiosyncratic shock as common across education and disability groups, which requires the residual to have zero mean within each of the six groups. That is not what we find. Table A.15 shows the raw residual means before any adjustment, and they rise systematically with disability severity: from 0.002 for non-disabled non-university workers to 0.069 for severely disabled non-university workers, and from 0.000 to 0.020 in the university group. A joint test that the six means are equal to one another, with person-clustered standard errors, rejects with a p-value of 0.0001. The wage equation's cross-equation restrictions therefore do not fully absorb disability-related wage levels. We handle this with a small weighted projection that removes the six cell means, along with aggregate time effects and a quadratic in the limitation score, before estimating

Table A.14: **Estimated Idiosyncratic Productivity Process**

Parameter	Estimate	Bootstrap SE
Persistence of the AR(1) component	0.8076	(0.0235)
Standard deviation of the innovation	0.1160	(0.0046)
Stationary standard deviation of the persistent component	0.1966	(0.0061)
Standard deviation of permanent heterogeneity	0.2322	(0.0071)
Standard deviation of the transitory shock	0.2125	(0.0028)

Notes: Estimated by minimum distance on the autocovariance structure of the second-stage wage residual, using 103,245 person-year observations on individuals observed in at least two consecutive waves. Standard errors are bootstrapped over individuals. The persistence and innovation variance in this table are the values used in the structural model; the three realised productivity states follow from a Tauchen discretisation of the estimated process.

Table A.15: **Residual Means by Education and Disability before the Projection**

Education	Disability	Observations	Raw weighted mean residual
Non-university	None	64,255	0.0019
Non-university	Moderate	4,504	0.0285
Non-university	Severe	1,700	0.0689
University	None	30,512	0.0005
University	Moderate	1,800	0.0023
University	Severe	474	0.0198

Notes: Weighted means of the raw second-stage wage residual within the six education-disability cells, before the orthogonalising projection described in the text. A joint test that all six cell means are zero, with person-clustered standard errors, gives $p = 0.0001$ and therefore rejects.

the shock process, so that the estimated process is free of disability-related level differences by construction. What we cannot claim, and do not, is that the residual was already orthogonal to the groups before that step. The projection is a construction step rather than a diagnostic that passed, and readers should treat the estimated shock process as conditional on it.

A.7 Elasticity of substitution

Building on the decomposition of the effects of disability on productivity, we further study the degree of substitutability between pure labour and experience by specifying an aggregate production technology. Understanding the degree of substitutability between labour and experience is important for assessing the aggregate consequences of disability. If the two inputs are close complements, disability-induced reductions in the supply of experienced workers place greater upward pressure on the relative price of experience, generating spillover effects for non-disabled workers. By contrast, if labour and experience are close substitutes, firms can more readily substitute between the two inputs, reducing price adjustments and mitigating the aggregate costs of disability-related labour force exit.

The representative firm in the aggregate economy is described by the following production function:

$$Y_t = A_t F(L_t, E_t) = A_t (L_t^\zeta + \delta E_t^\zeta)^{\frac{1}{\zeta}}, \quad (14)$$

In Equation 14, output is denoted by Y_t , total factor productivity by A_t , aggregate labour input by L_t , and aggregate experience by E_t . The parameters δ and ζ capture, respectively, the relative efficiency of experience and the degree of substitutability between labour and experience. The production function follows a constant-elasticity-of-substitution (CES) form, where the elasticity of substitution is $\sigma = \frac{1}{1-\zeta}$. Values of $\zeta = 1$ imply perfect substitutability, values of $0 < \zeta < 1$ imply imperfect substitutability, $\zeta = 0$ corresponds to Cobb-Douglas production, and $\zeta < 0$ implies complementarity between labour and experience.

To estimate the parameters δ and ζ , we adopt the identification strategy employed by [Katz and Murphy \(1992\)](#), [Jeong, Kim and Manovskii \(2015\)](#) and [Kim and Rhee \(2022\)](#). Using HILDA Survey data on weekly working hours and coefficients derived from Equation 3, we convert weekly hours into annual hours by multiplying by 52 and construct aggregate measures of pure labour and effective experience by aggregating across individuals in period t :

$$\hat{L}_t = \sum_i \hat{l}_{it} \hat{z}_{it} h_{it} = \sum_i \hat{\lambda}_L(j, dis_{it}, edu_{it}) \cdot h_{it} \quad (15)$$

and

$$\hat{E}_t = \sum_i \hat{e}_{it} \hat{z}_{it} h_{it} = \sum_i \hat{\lambda}_E(j, dis_{it}, edu_{it}) \cdot \hat{g}(e) \cdot h_{it}, \quad (16)$$

In these expressions, $\hat{l}_{it}$ and $\hat{e}_{it}$ denote the components of labour and effective experience, respectively, while z_{it} captures productivity effects from other explanatory factors, and h_{it} indicates the annual hours worked by individual i at time t . The time-series data of relative supply of experience, $\frac{\hat{E}_t}{\hat{L}_t}$, are then calculated. Next, the relative price of experience to labour is defined as $\Pi_{E_t} \equiv \frac{F_{E_t}}{F_{L_t}}$, where workers are assumed to be paid their marginal products in a competitive market. Using the functional form specified in Equation 14, the relative price of experience can be written as $\Pi_{E_t} = \delta \left(\frac{E_t}{L_t} \right)^{\zeta-1}$. Taking the natural logs yields

$$\ln(\Pi_{E_t}) = \ln(\delta) + (\zeta - 1) \ln \left(\frac{E_t}{L_t} \right), \quad (17)$$

in which parameters δ and ζ can be estimated using a linear regression. Quadratic time effects are incorporated in the regression by allowing the intercept to be a quadratic function of time, with $\delta_t = \delta + \eta_1 t + \eta_2 t^2$, capturing demand shifts between the production factors over time.

Figure A.3 plots the longitudinal trends of relative price of experience (left axis) and relative supply of experience (right axis) from 2002-2003 (wave 3) to 2023-2024 (wave 24)⁶. Over the sample period the relative supply of experience falls steadily, from 5.39 in 2002-03 to 4.56 in 2023-24, a decline of about 15 per cent. The relative price of experience does not move with it in any simple way: it rises from 0.056 at the start of the period to a peak of 0.087 in 2009-10, then drifts back to 0.065 by the end, leaving no clear trend over the full period. A steadily falling relative supply paired with a roughly flat relative price is what we would

⁶The instrument “household errands” is not collected in wave 1 of the HILDA Survey. Consequently, the one-year lagged instrument is unavailable for wave 2 observations, which are excluded from the main estimation sample. The analysis therefore uses waves 3 onward.

Table A.16: 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)	0.2172	(0.4461)	(0.5976)	[1.0669]	- - -
Linear trend	-6.2101	(3.2774)	(2.9128)	[3.1660]	0.161
Quadratic trend	3.3763	(4.3700)	(3.5521)	[3.4095]	- - -
First differences	1.0316	(3.5486)	(2.5725)	[3.6363]	- - -
Waves (levels / first differences)	22 / 21				

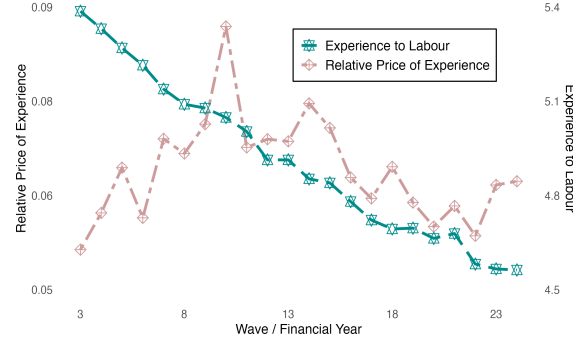
Notes: This table reports the slope on the log relative supply of experience in the CES price regression, estimated on waves 3-24 of the HILDA Survey. The dependent variable is the log relative price of experience; both sides are constructed from the estimated wage model. The four rows differ only in how time is handled: no trend, a linear trend, a quadratic trend, and first differences. Each slope is shown with ordinary least squares standard errors in parentheses, Newey-West standard errors with two lags, and two-step bootstrap standard errors in square brackets that re-estimate the probit, the wage equation and all four price regressions on every resampled panel. The implied elasticity of substitution is $1/(1-\zeta)$ and is reported only where the slope is negative, since a non-negative slope has no admissible CES interpretation. No slope is significant under all three standard errors, and the sign of the slope changes across specifications, so the elasticity is not identified in this sample.

expect if demand for experience-intensive labour were also drifting down over the period, but the two series alone cannot separate movements along a demand curve from shifts in it.

Table A.16 reports the slope on log relative supply under four specifications: the simple regression of Kim and Rhee (2022), a linear time trend in the intercept, the quadratic trend of Equation 17, and the same relationship in first differences. Each slope is reported with three standard errors: ordinary least squares, Newey-West errors that allow for serial correlation in the 22 annual observations, and two-step bootstrap errors that re-run the entire estimation chain, probit and wage equation included, on every resampled panel. In the CES interpretation the slope equals $\zeta - 1 = -1/\sigma$, so only a negative slope maps into an admissible elasticity. Three of the four specifications deliver a positive slope, which is inadmissible, and the one negative slope, -6.21 under the linear trend, implies an implausibly low elasticity of 0.16. Only one slope comes anywhere near conventional significance: the linear-trend slope has a ratio to its standard error of 1.9 under ordinary least squares, 2.1 under Newey-West and 2.0 under the bootstrap, so it clears the five per cent threshold on one of the three and misses it on the other two. Every other slope has a ratio below one. The bootstrap errors, which are the only ones that account for the fact that both sides of the regression are themselves estimated, are the largest of the three in three of the four specifications. We therefore conclude that the elasticity of substitution between pure labour and accumulated experience is not identified in this sample, and we report the table as evidence of that rather than as an estimate of σ . The reason is visible in the two series themselves. With 22 annual observations, a relative supply series that moves slowly and monotonically, and a relative price series constructed from the same wage equation, there is too little independent variation left to separate the slope from the trend.

This has two implications for the rest of the paper. First, nothing in the structural model depends on this elasticity. The production side of the model is Cobb-Douglas in capital and effective labour, and the labour and experience components enter through the estimated efficiency profiles rather than as separate inputs with an estimated substitution elasticity between them, so the results in Section 4 are unaffected. Second, the question is worth returning to with data better suited to it. Whether the aggregate cost of disability-related withdrawal from work is amplified or absorbed depends on how readily firms substitute between inexperienced and experienced labour, and a longer series, or variation across industries or regions rather than over time alone, would give that question the variation it needs.

Figure A.3: Relative Price and Supply of Experience to Labour over Time



Notes: The x-axis represents financial years, labeled as waves in the HILDA Survey, with wave 3 corresponding to the financial year 2002-2003 and wave 24 to 2023-2024. The quantities of labour and experience, which are used to compute the experience to labour ratio, are expressed in annual terms, calculated by multiplying estimated efficiency units by the total annual hours worked. The latter is derived from the HILDA Survey variable with the label "DV: Hours per week usually worked in all jobs".

Because the slope is not identified here, we cannot use these data to place the Australian production structure on either side of the existing evidence, and we do not claim to. It is worth recording what that evidence says, because it sets the range a better-identified estimate would be compared against. [Katz and Murphy \(1992\)](#) regress the log relative wage of older male workers, those with 26-35 years of experience, on the log relative supply of older to younger workers, and their coefficient of -0.348 implies an elasticity of substitution of about 2.87. Studies of substitution between high- and low-skilled labour, or between college and high-school equivalent labour, report elasticities above unity, commonly between 1.6 and 3.5 (for example [Autor, Katz and Kearney \(2008\)](#) and [Acemoglu and Autor \(2011\)](#)), and panel and micro-level estimates across countries tend to fall between roughly 1.7 and 2.6 (for example [Jerzmanowski and Tamura \(2023\)](#) and [Behar \(2025\)](#)). Against this, [Jeong, Kim and Manovskii \(2015\)](#) and [Kim and Rhee \(2022\)](#) conclude that labour and experience are complements in aggregate U.S. production functions. The literature is therefore not settled even for the United States, and an Australian estimate would be a useful addition to it once the identification problem is solved.

What our estimates do show, and what does not depend on the elasticity, is the pattern in the two underlying series. The relative supply of experience has fallen steadily over the past two decades while its relative price has not risen, and for workers with disabilities that combination matters regardless of how the production function is specified. Their experience accumulation is already limited by lower employment rates and weaker attachment to work, so a return to experience that is at best flat over time compounds the disadvantage: it reduces not only how much experience they accumulate over a career, but the wage payoff to whatever they do accumulate.

B Structural analysis

B.1 Equilibrium

Given the Australian tax-and-transfer system, the population growth rate n , and the interest rate r , a stationary competitive equilibrium consists of:

- (1) a set of individual policy functions $\{c_j(x_j), l_j(x_j), a_{j+1}(x_j)\}_{j=1}^J$ that solve the individual's optimisation problem described in Equation 7 for states x_j ;
- (2) aggregate inputs of capital K and effective labour H chosen by the representative firm to solve the static profit-maximisation problem;
- (3) aggregate bequests, comprising the assets of individuals who die before the terminal age together with the terminal balances chosen at age J , are fully redistributed with interest as uniform lump-sum transfers, so that total bequests B equal the total assets left behind:

$$B = \sum_j \frac{\mu_{j-1}(1 - \psi_j)}{1 + n} \int a_j(x_j) d\Phi_j(x_j), \quad (18)$$

where $\Phi_j(x_j)$ denotes the time-invariant distribution of states x_j at age j .

- (4) the current account is balanced and the small-open-economy assumption pins the domestic interest rate to $r = \bar{r}$, with net foreign assets a_f adjusting freely to satisfy the economy's resource constraint;
- (5) goods and factor markets clear:

$$K = \sum_j \mu_j \int a_j(x_j) d\Phi_j(x_j) + B + a_f \quad (19)$$

$$H = \sum_j \mu_j \int h_j(x_j) d\Phi_j(x_j) \quad (20)$$

where $h_j(x_j) \equiv (1 - l_j(x_j))e_j(x_j)$ is individual effective labour supply, and factor prices are determined competitively according to their marginal products:

$$w = (1 - \alpha)A \left(\frac{K}{H} \right)^\alpha, \quad q = \alpha A \left(\frac{K}{H} \right)^{\alpha-1}, \quad r = q - \delta; \quad (21)$$

- (6) the government budget constraint holds with equality, as stated in Equation 6.

B.2 Calibration

Table B.1 summarises the calibration, combining parameters constructed directly from Australian data with parameters taken from the literature or chosen internally to match model moments. The population growth rate is consistent with ABS pre-COVID population growth rates and close to the annual growth observed in the late 2010s. Survival probabilities are constructed from the ABS 2015-2017 Life Tables: in the data construction, age-specific male and female death probabilities are averaged and converted to one-year survival probabilities. The government expenditure share is computed from IMF World Economic Outlook general government expenditure as a share of GDP, averaged over 2010-2019, while the government bond share is computed from IMF World Economic Outlook net debt as a share of GDP over the same period. The

income-tax curvature parameter corresponds to the average value of the Australian tax-progressivity estimates reported by [Tran and Zakariyya \(2022\)](#). Pension and DSP policy parameters are taken from Services Australia schedules applicable in 2018 and are converted into model units using the benchmark scaling factor. The participation costs, the work-hour disutility weights, the DSP schedule multiplier and the income-tax scaling parameter are set internally; the preference parameters are fixed at standard values. The work-cost and work-disutility parameters are chosen to match the life-cycle employment and average-hours profiles of each of the six education-disability groups, the DSP schedule multiplier and the severe-disability work-cost terms are chosen to match the age profile of DSP receipt, the income-tax scaling parameter adjusts to balance the government budget, and the wage rate follows from the firm’s first-order conditions at the world interest rate. The persistence and innovation variance of the idiosyncratic productivity process are estimated directly from the second-stage wage residuals of Section 3 rather than taken from the literature, and the three realised productivity states follow from the Tauchen discretisation of that estimated process.

The internal calibration proceeds in two alternating stages, holding prices, the tax scale and the bequest transfer at their converged benchmark values. In the first stage, the work-hour disutility weight and the three participation-cost knots of each education-disability type are chosen by minimum distance on that type’s hours and employment profiles, using a damped Gauss-Newton search with bound constraints. In the second stage, the DSP schedule multiplier is chosen by a coarse-to-fine grid search against the composition-weighted DSP participation profile. The two stages alternate until no parameter moves, and the general equilibrium is then re-solved at the calibrated values, so every moment reported in the paper comes from a fully re-closed equilibrium rather than from the fixed-price search.

B.3 Model fit

The benchmark is calibrated to the life-cycle profiles of weekly hours and employment for each of the six education-disability groups, and to the age profile of DSP participation. Table B.2 reports the resulting errors group by group. The fit is closest for the two non-disabled groups, with hours errors of under two weekly hours and employment errors of three to five percentage points, and loosest for severely disabled university graduates, at 4.5 hours and 11.9 percentage points. That ordering follows cell size. Severely disabled university graduates are under one per cent of the working-age population, so their empirical profile is volatile from year to year, and the calibration deliberately does not chase it at the cost of the other five groups. The residual error is also concentrated at particular ages rather than spread evenly. It is largest between ages 62 and 64, where the data show a withdrawal from work that the model does not reproduce because it contains no early retirement and no transition from the DSP to the Age Pension. Counterfactual effects at those ages should therefore be read with more caution than effects earlier in working life. The third column of the table reports the moment the model was not calibrated to. Annual labour earnings are matched to within 10 to 15 per cent of the group mean for the two non-disabled groups and to within 21 to 23 per cent for the two moderately disabled groups, with the largest errors again in the severe state, at 31 per cent for non-university and 40 per cent for university workers. Mean levels are closer than those figures suggest. Averaged over ages 22 to 64 the model reproduces group mean earnings to within 3 to 20 per cent, and within 10 per cent for the three largest groups, so the error is mostly in the shape of the age profile rather than its level: the model’s earnings profile peaks earlier and falls away faster than the data at the end of working life, which is the same age range where the hours and employment profiles diverge. We did not recalibrate to close this gap, and it is worth being explicit about why. The parameters that could be moved are the work costs and the work-hour disutility terms, and both are already pinned down by the hours

Table B.1: Calibration: External and Internal Parameters

Parameter description	Parameter value	Source/Target
<i>Demographics</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
<i>Preferences</i>		
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, Tran and Woodland (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	$\phi_1 = -9.5$	De Nardi (2004)
Degree of luxury	$\phi_2 = 11.6$	De Nardi (2004)
<i>Endowments</i>		
Deterministic labour productivity	$e_{j,\varepsilon_D,\varepsilon_E}$	Empirical analysis
Shock: persistence	$\rho = 0.8076$	HILDA wage residuals
Shock: innovation variance	$\sigma_\eta^2 = 0.0134$	HILDA wage residuals
Shock: realised productivity	$\eta(z_j) = \{0.729, 0.979, 1.315\}$	Tauchen discretisation of the estimated process
Wage rate	$w = 1.5463$	- - -
Labour force participation cost	$\bar{n}_j(\varepsilon_D, \varepsilon_E)$	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	$\kappa_{D,\text{age}} = 0.10$	DSP recipient ratio
Initial distributions		
<i>Education</i>	$\mu_{j=1}^{\varepsilon_E} = \{0.81, 0.19\}$	HILDA
<i>Disability</i>	$\mu_{j=1}^{\varepsilon_D} = \{0.92, 0.05, 0.03\}$	HILDA
<i>Assets</i>	$\mu_{j=1}^a$	HILDA
Joint distributions	$\mu_j^{\varepsilon_E, \varepsilon_D}$	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	$\lambda = 0.6055$	- - -
Government expenditure share	$G/Y = 0.229$	IMF WEO
Government bond share	$B/Y = 0.186$	IMF WEO
Income test taper rate	$\omega^y = 0.5$	Services Australia (2018 rates)
Assets test taper rate	$\omega^a = 0.003$	Services Australia (2018 rates)
Maximum pension (in model unit)	$p^{\max} = 0.0420$	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)	$\bar{a}_1 = 0.5010$	Services Australia (2018 rates)
Hours threshold	$\bar{h} = 15$	Services Australia (2018 rates)
DSP income test taper rate	$\omega_D^y = 0.5$	Services Australia (2018 rates)
DSP assets test taper rate	$\omega_D^a = 0.003$	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	$\varepsilon_D = \text{SD}$	Assumed medical test

Notes: ABS: Australian Bureau of Statistics, ATO: Australian Taxation Office, IMF WEO: International Monetary Fund World Economic Outlook, SOE: Small open economy. Services Australia entries refer to policy settings applicable in 2018.

Table B.2: **Benchmark Calibration Fit by Group**

Group	Hours RMSE (weekly)	Employment RMSE (pp)	Earnings RMSE (AUD)	Earnings RMSE (% of mean)
Non-university, no disability	1.91	5.21	6,425	14.5
Non-university, moderate disability	3.24	9.15	4,783	20.6
Non-university, severe disability	2.72	7.81	2,389	30.9
University, no disability	1.61	3.44	7,401	10.3
University, moderate disability	3.33	6.40	11,323	22.9
University, severe disability	4.47	11.94	8,948	40.0
DSP participation	- - -	1.98	- - -	- - -

Notes: Root mean squared errors between the model-generated and HILDA life-cycle profiles over ages 22 to 64, evaluated at the converged general-equilibrium allocation. Hours and earnings are unconditional group means at each age, counting the non-employed at zero; employment errors are in percentage points. Earnings are in real 2018-19 AUD, and the final column expresses the same error as a share of the group’s mean earnings over these ages. Hours and employment are calibration targets. Earnings are not: they follow from the calibrated labour supply, the estimated efficiency profiles and the equilibrium wage, and are reported here as a check on the model. The DSP row compares model DSP participation with the HILDA recipient ratio over the same ages.

and employment profiles; targeting earnings as well would trade a better earnings fit for a worse fit on the two margins the counterfactuals actually operate through. The wage side of earnings is not free either: the efficiency profiles come from the empirical section and the wage per efficiency unit clears the labour market. Reporting earnings as a validation moment is therefore more informative than fitting it.

The benchmark equilibrium also satisfies the aggregate conditions imposed on it. The tax-function scaling parameter adjusts to balance the government budget, leaving a residual of less than two parts in a million of output, and the economy’s resource constraint holds to within two parts in ten thousand of output. The solution passes all 54 invariant checks run at the end of the benchmark solve, which cover the household budget identity, the means-test schedules, the bequest transfer and the market-clearing conditions. These are reported in the run manifest that accompanies the replication code.

B.4 Numerical accuracy

Table B.3 reports how the benchmark solution moves when the numerical grids are refined. The result is mixed, and worth stating precisely. First, the aggregates are stable: effective labour moves by at most 0.14 per cent and household assets by at most 1.4 per cent across the three refinements, so the quantities the counterfactuals are built on do not depend on the grid. Second, the individual life-cycle profiles are less stable. Weekly hours move by 1.0 to 1.5 hours in root mean square and employment rates by 3.5 to 5.3 percentage points, which exceeds the tolerances we set in advance. The reason is that employment is a discrete choice. Refining the grid moves marginal households across the participation threshold, and each such household contributes a full percentage point of movement in its own cell rather than a marginal adjustment. We therefore do not claim that the solution is grid-independent at the level of individual profiles. What can be said is that the movement is smaller than the model’s own distance from the data, which is 1.6 to 4.5 hours and 3.4 to 11.9 percentage points in Table B.2, so grid refinement does not change any conclusion the paper draws from those profiles. Refining the grids further is possible but expensive: the solution time rises roughly with the product of the grid sizes, and the aggregates, which is what the counterfactuals compare, are already stable to within about one per cent.

Table B.3: Sensitivity of the Benchmark Solution to the Numerical Grids

Configuration	Hours RMS	Employment RMS (pp)	DSP RMS (pp)	H (%)	K (%)
Saving grid density doubled	1.02	3.48	0.19	0.11	0.67
State grid doubled, 50 to 100 points	1.36	4.87	0.55	0.02	1.38
Asset grid upper bound raised by half	1.45	5.32	0.37	0.14	0.01
Stated tolerance	0.50	1.00	1.00	1.00	1.00

Notes: Each row changes one numerical setting and re-solves the household problem from scratch, holding prices, the fiscal schedules, bequests and every calibrated parameter at their converged benchmark values. The first four columns report root mean squared deviations from the benchmark solution across ages and groups; the last two report the absolute percentage deviation in aggregate effective labour and in household assets. The final row is the tolerance set in advance for the claim that the solution is grid-independent.

B.5 Aggregate outcomes

Table B.4 shows that the two counterfactuals are of very different aggregate size. Removing the experience component in Experiment 1 lowers effective labour and the return to working over the life cycle, and the aggregate effects are large: output falls from AUD 62,862 to AUD 45,932 per capita, a decline of 27%, with annual net saving falling by 37% and consumption by 21%. Average weekly hours fall only slightly, from 23.47 to 23.01, which is the point of the experiment: the loss is a loss of productivity per hour worked rather than of hours, so households cannot undo much of it by working more. Welfare falls for every education-disability group. Removing the DSP in Experiment 2 barely moves the aggregates at all. Output rises by 0.2%, consumption by 0.1%, and average weekly hours by 0.05 hours. This is a composition effect rather than a small behavioural response: the severely disabled are about 7% of the working-age population in the model, so even the large increases in their own labour supply reported in Table 4 leave the population aggregates almost unchanged. The welfare results follow the same logic. Under the benchmark price vector the problems of the non-disabled and moderately disabled groups are unaffected by DSP removal, so their welfare is identical to the benchmark by construction rather than as a finding. Non-university severely disabled individuals lose, as expected: they give up transfer income and leisure and gain market income. University severely disabled individuals are close to indifferent, and by this measure marginally better off, because most of them are already partly tapered out of the payment while still facing the distortion created by the fifteen-hour rule; removing the payment removes the distortion along with the transfer. The two effects nearly cancel for that group, which is worth keeping in view when reading the large labour-income response in Table 4 as a measure of the program's cost.

Table B.4: **Benchmark and Counterfactual Aggregates**

	Benchmark	Experiment 1	Experiment 2
Real Output Per Capita (AUD)	62,862	45,932	62,972
Annual Net Saving Per Capita (AUD)	3,154.5	1,985.0	3,159.9
Labour (Weekly Hours)	23.47	23.01	23.52
Real Consumption Per Capita (AUD)	25,728	20,360	25,760
Welfare (Model Utility)			
Overall	-189.10	-225.31	-189.71
Non-university, Non-disabled	-185.70	-223.69	-185.70
Non-university, Moderately disabled	-272.61	-327.62	-272.61
Non-university, Severely disabled	-416.63	-463.08	-435.67
University, Non-disabled	-144.21	-167.59	-144.21
University, Moderately Disabled	-172.43	-203.11	-172.43
University, Severely Disabled	-255.76	-288.22	-254.82

Notes: Experiment 1 removes the estimated experience component from labour productivity, whereas Experiment 2 sets the maximum DSP payment to zero. The benchmark is the general-equilibrium allocation. The counterfactual household problems hold the benchmark wage, interest rate, bequests, income-tax scaling parameter and model scale fixed. Monetary outcomes are converted from model units to annual real AUD using the exchange rate that matches mean labour income at age 50 in the model to its HILDA counterpart. Output is obtained from the production function using population-weighted effective labour and the capital demand implied by the world interest rate. Annual net saving per capita is the flow $S_t = (1 + g)K_{t+1} - K_t$. Weekly labour hours equal the population-weighted non-leisure share multiplied by 168, and consumption is the population-weighted mean of individual consumption. Overall welfare is the population-weighted mean of individual value functions, $\sum_i V_i \mu_i / \sum_i \mu_i$. Group welfare applies the same calculation conditional on education and disability status. Because utility levels are negative under the adopted normalisation, a higher (less negative) value denotes greater welfare.