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The Social Dividend

An Actuarial Case for Higher Income Support

A report to inform the Economic Inclusion Advisory Committee 2025

Report to Government

DECEMBER 2024

Contents

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This document is intended for general informational purposes only. The analysis in this report was commissioned by the Economic Inclusion Advisory Committee within the Commonwealth Department of Social Services and prepared by Mandala.

Mandala is an economics research and advisory firm. Mandala specialises in combining cutting-edge data and advanced analytical techniques to generate new insights and fresh perspectives on the challenges facing businesses and governments.

The analysis produced in this document is current as of the date below and may be subject to change.

Note: All dollar figures are Australian dollars unless indicated otherwise.

Executive summary

Increasing JobSeeker is an investment which provides economic benefits, social benefits and critical efficiency savings.

There has been much research on the economic benefits of increasing JobSeeker, but much less research on the social benefits and efficiency savings. This report seeks to fill this gap by combining actuarial techniques with microdata and econometric analysis.

The key finding of the report is this: increasing JobSeeker to 90% of the Age Pension would deliver a social return of 24% and deliver key efficiency savings which outweigh any potential reduction in job search intensity.

Every $100 invested in an increased JobSeeker payment delivers a $24 social return. This includes a range of physical health benefits, mental health benefits, and intergenerational benefits through positive impacts on childhood development.

There are efficiency benefits, too, through avoided hospitalisations, fewer GP visits, lower mental healthcare costs, fewer justice system interactions and lower children's lifetime social security system use.

Importantly, these efficiency savings outweigh even the most generous estimates of any potential reduction in job search intensity – which is already unlikely in Australia given that a higher JobSeeker payment will remain much lower than average wages.

The JobSeeker Payment is below all poverty measures in Australia

Around 830,000 people – 5% of the comparable working-age population – are receiving JobSeeker. Single JobSeekers receive $389 a week, much lower than the average wage in Australia of $1,923. This puts JobSeeker recipients below all of Australia's poverty measures. Australia ranks the second-lowest in the OECD in terms of its support to unemployed people after two-months.

The low payment is correlated with poorer outcomes for recipients and their children

Microdata analysis shows that JobSeeker recipients exhibit higher rates of death by suicide, financial stress, severe psychological distress and risk of homelessness than the broader population. They report worsening physical health, poor nutrition and an inability to afford medicines, healthcare and meals.

Research shows that increasing JobSeeker would grow the economy and create jobs

Unmet consumption needs mean people on low-incomes spend more of their income than people on high incomes (who save more). Increasing JobSeeker supports the economy, including through this secondary spending. JobSeeker is also an 'automatic stabiliser' because it results in more government spending during economic downturns (when unemployment is high). Deloitte Access Economics estimates that increasing JobSeeker by $75 a week would grow the economy by $4 billion and create 12,000 jobs. These results, however, did not quantify social benefits.

Quantifying social benefits, the social return from increasing JobSeeker exceeds 24%

This report combines actuarial techniques with micro-datasets (HILDA, PLIDA, DOMINO) and leading econometric research to measure the impact of increasing JobSeeker to 90% of the Age Pension (from the current $389 per week to $515 per week for singles). This increase halves the poverty rate of JobSeekers.

This study finds that increasing JobSeeker would deliver a social return of more than 24%. This return quantifies physical and mental health improvements and childhood development impacts. Every $100 invested in an increased JobSeeker payment delivers a $24 social return. These benefits accrue to the Government, the individuals and society. Importantly, the efficiency benefits far outweigh any efficiency costs.

Increasing JobSeeker provides efficiency savings which outweigh even the most generous estimates of reduced job search intensity

Almost a quarter of the social return comes in the form of government efficiency savings. Increasing JobSeeker results in avoided hospitalisations, fewer GP visits, lower mental healthcare costs, fewer justice system interactions and lower children's lifetime social security system use.

Increasing JobSeeker is unlikely to result in people staying on JobSeeker for a longer duration given that, even with the increase, it is still far below the replacement rate. However, even if people did stay on JobSeeker for longer, the efficiency benefits to Government would outweigh these costs under even the most generous estimates from the international literature.

Increasing JobSeeker provides benefits to individuals and children

Just over a quarter of the social return accrues to JobSeeker recipients and their families. This includes improved mental-health related quality adjusted life years, increased earnings when they become employed and avoided out-of-pocket mental health costs.

Increasing JobSeeker provides broader benefits to society

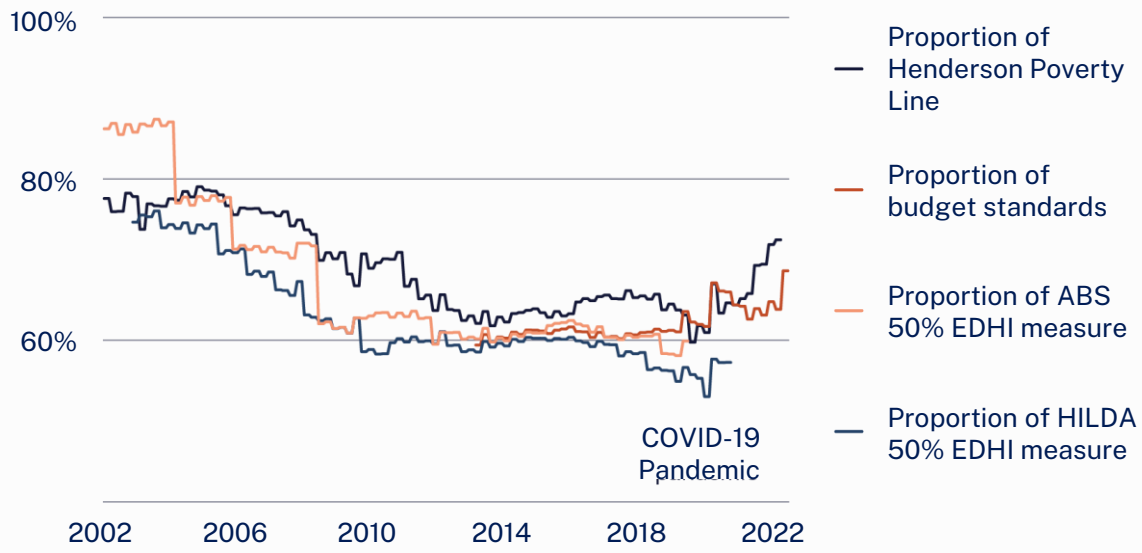
More than half of the social return accrues to broader society through avoided lives lost due to suicide, avoided childhood poverty, avoided adolescent justice interactions, avoided insurer mental health costs, and productivity gains to GDP.

This report does not consider all potential benefits of increasing JobSeeker. But including the social benefits along with the economic benefits is key to unpacking the overall impact of increasing JobSeeker.

The JobSeeker Payment is below all poverty measures, and is far below the OECD average, which may not adequately support transitions back into employment

Exhibit 1: The JobSeeker Payment is below all poverty measures

% of poverty measure, Australia, 2002-2023



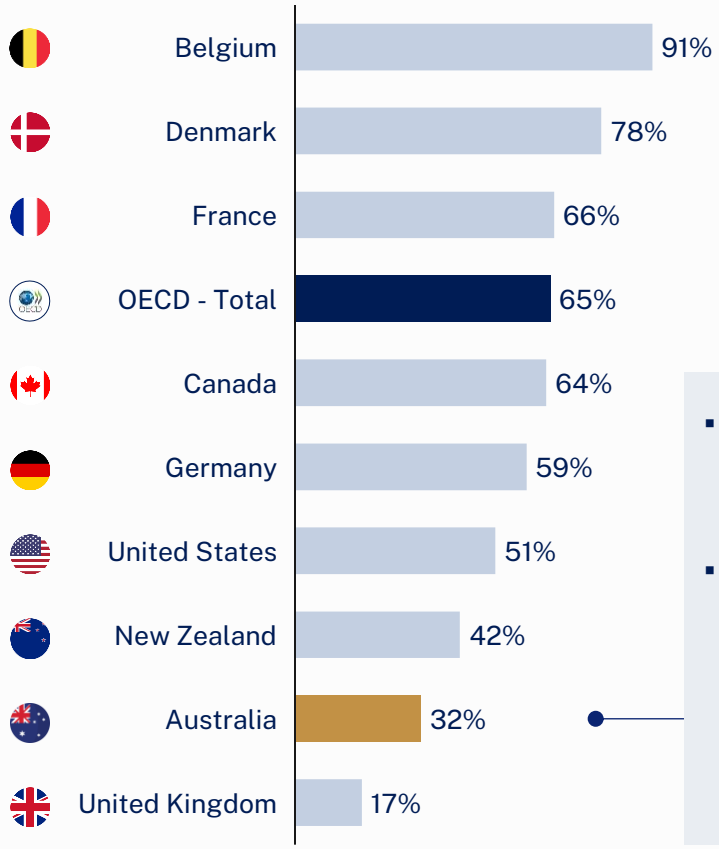
The Economic Inclusion Advisory Committee has judged that the current JobSeeker Payment rate may be a **net negative for participation**, with poverty being a barrier to employment.

Recent increases have not addressed this. Compared to the average wage in Australia of $1,923 per week, JobSeekers must try to survive and re-find work on just $393.[1] A poll of Australians, showed 68% agreed income support should be above the poverty line.[2]

1 ACOSS (2024) *Woefully low JobSeeker payment just 20% of average wage.* 2 ACOSS (2022).
Source: Economic Inclusion Advisory Committee (2024) 2024 Report to Government; Mandala analysis.

Exhibit 2: Australia's unemployment support is far below the OECD average

After 2 months, unemployment benefit % of prior in-work income, 2022



- Australia's replacement rate at 2 months is the second lowest in the OECD.
- If looking longer term (beyond a 2-month comparison), Australia's replacement rate after 2 years (32%) remains below the OECD average (35%) after 2 years.

Source: OECD (2024) *Benefits in unemployment, share of previous income*; Mandala analysis.

The JobSeeker Payment's current rate puts 830,000 Australians at risk, around 5% of working-age people

Over 830,000 people currently receive the JobSeeker Payment. This is the main income support payment for recipients aged between 22 years and the pension age. JobSeeker is targeted to people who are looking for work or who temporarily cannot work due to injury or illness or bereavement; who fall under means-testing levels.[1]

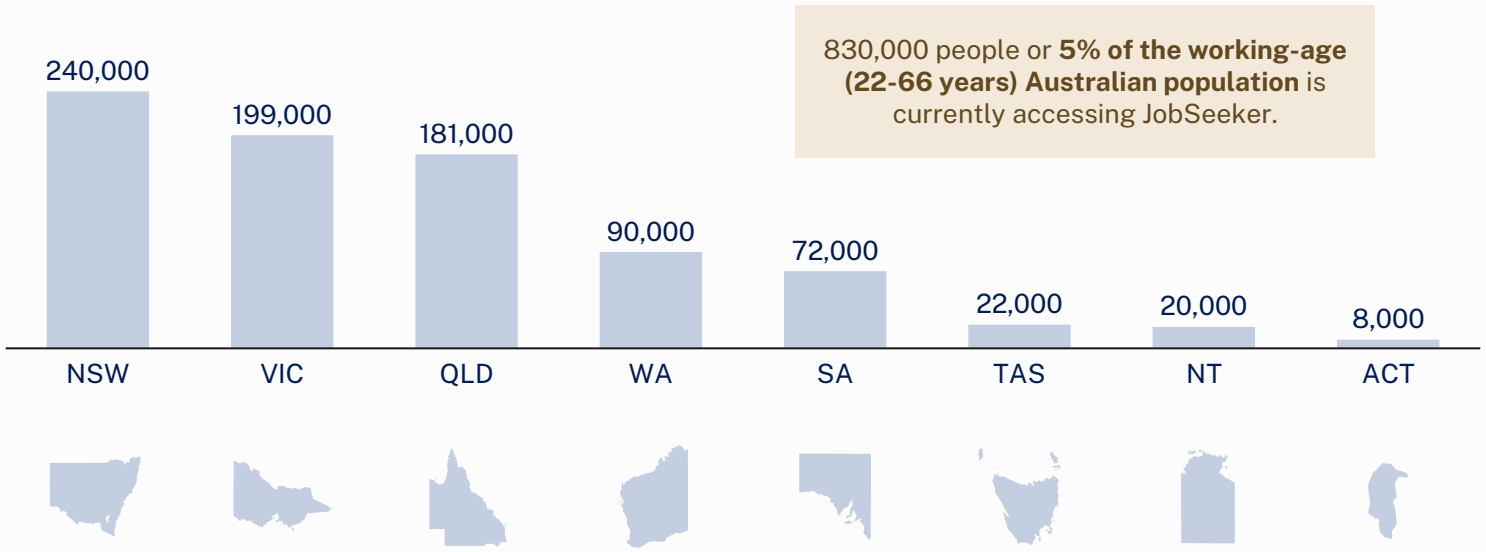
Around 54% of current JobSeeker Payment recipients are male, half of JobSeeker recipients are aged 45 to 67 years old. Four in ten JobSeeker recipients have partial capacity to work (for less than 30 hours a week). Four in ten have been on the JobSeeker for under one year. Three in ten are based in New South Wales. Two in ten reported some earnings in the last fortnight, and a correlated portion received the part-rate of Payment. One in ten was either suspended or paid a zero rate.[2]

This data represents the stock of JobSeeker recipients. Comparing flows in the year to 30 June 2023, 325,300 people started receiving JobSeeker. A majority (58%) of these entrants exited JobSeeker within twelve months, and did not return to the JobSeeker Payment in the following twelve months.[3]

Note: Working-age is defined as 22-66 year olds to align with JobSeeker eligibility from 22 to the pension age (67).
1 DSS (2020) *Jobseeker Payment.*
2 DSS (2024) *Monthly time series.*
3 DSS (2024) *DSS Benefit and Payment Recipient Demographics - quarterly data.*

Exhibit 3: 830,000 people are currently accessing JobSeeker across Australia

Number of recipients, 25 October 2024



OF THE JOBSEEKER RECIPIENTS IN AUSTRALIA:

- **185k** *received a part or zero rate (22%)*
- **569k** *are 35 years or older (68%)*
- **353k** *have partial capacity to work (42%)*
- **59k** *had children under 18 years (7%)*[1]

1 Data for children under 18 years is from June 2024 DOMINO microdata. All other figures are from DSS Monthly Time Series data as of October 2024.
Source: DSS (2024) *Monthly Time Series;* Mandala analysis.

The Economic Inclusion Advisory Committee has twice advocated to raise the JobSeeker level

In both the Economic Inclusion Advisory Committee's 2023 and 2024 reports to Government, the Committee has proposed an increase to JobSeeker to restore its relativities with the Age Pension from the 1990s.

The Committee raises serious concerns about the adequacy of working-age income support payments.

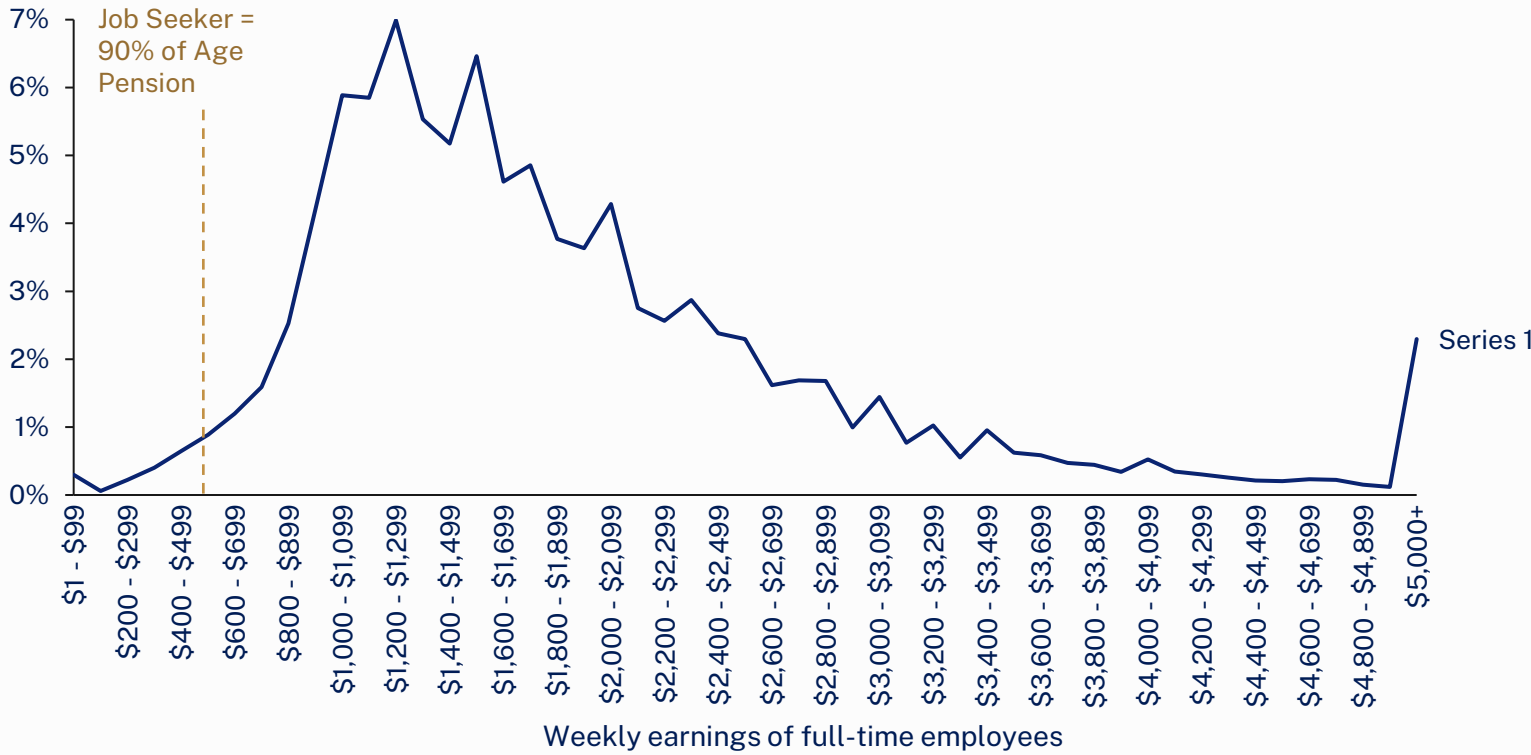
Current rates are inadequate when measured relative to pensions, the minimum wage or against a range of income poverty measures. Due to severe financial stress, some recipients are having to choose between paying for their medicine or electricity bills.

An increase to the rate of JobSeeker would still place it below the 3rd percentile of the weekly earnings distribution. That is, more than 97.5% of full-time employees would be earning more than the JobSeeker Payment recipient.

Because of the difference in levels of income between JobSeekers and those employed, the Committee's recommendation challenges the notion that a raise to JobSeeker would disincentivise participation.

Exhibit 4: At 90% of the Age Pension, JobSeeker would be at just above the 2nd percentile of the income distribution

JobSeeker increase compared against the distribution of weekly earnings of full-time employees, Australia, 2023



The **Economic Inclusion Advisory Committee (2024)'s** research shows that at 90% of the Age Pension, 97.5% of full-time employees would still earn more than JobSeekers.

The low level of JobSeeker relative to labour market earnings likely to be obtained by jobseekers means that the increase to JobSeeker to 90% of the Age Pension is not likely to disincentivise shifts into employment.

Source: Economic Inclusion Advisory Committee (2024) *2024 Report to Government;* ABS (August 2023) *Employee Earnings*, Mandala analysis.

A higher rate is unlikely to affect JobSeeker numbers due to strict means-testing and obligations on job search

Australia's JobSeeker Payment system is highly targeted to the most disadvantaged. JobSeeker eligibility is subject to income and assets testing for individuals and their partners.

Recipients of JobSeeker are therefore some of the most disadvantaged people in a mostly otherwise wealthy nation. Compared to other countries, Whiteford (2017) notes that cash benefits in Australia are more targeted to the poorest 20% of the population than any other OECD country.[1]

After meeting the eligibility criteria to receive JobSeeker, JobSeeker recipients must meet strict obligation requirements on job search activity. The requirements include onerous reporting requirements and mandatory targets around job search activity. Suspension occurs when strict mutual obligation requirements are not met.

Even at 90% of the Age Pension, the JobSeeker payment will be significantly lower than average wages. Discussed further below, this means an increase in JobSeeker is unlikely to disincentivise participation.

Exhibit 5: JobSeeker is highly targeted to low-income recipients

Eligibility criteria

- Must be **unemployed** or earn less than $740 per week[1]
- **Partner income** less than $1,290 per week
- **Liquid assets** less than $5,000[2]
- **Must be a permanent resident and in Australia for 4+ years**

Mutual obligations[3]

Agree a Job Plan with Employment Services
- Agree to a Job Plan
- Attend appointments with an Employment Services provider

Meet requirements of Job Plan
- Meet points target for applications, training and job interviews.
- Failing to meet the target will incur demerits or a penalty.

Obligation to interview and accept
- Attend all job interviews
- Accept any offer of suitable paid work
- Not leave a job or training, without a valid reason

Report own & partners' income fortnightly
- Report income in the past 14 days, including partner income. Report even if it's $0.
- Report if you move or starting a new relationship.

Failing to satisfy all obligations results in payment suspension.

1 Sole traders face more complex income-testing procedures intended to limit access to payments.
2 If you have higher liquid assets, there will be a waiting period of between one and 13 weeks. Those paid a lump sum to cover leave or redundancy face a preclusion period.
3 Those with partial capacity to work, principal carers and those aged over 55 may have different requirements. Source: DSS (2024) *Income and assets tests;* DSS (2024) *Mutual obligation requirements*

1 The JobSeeker Payment (JobSeeker) is below all poverty measures, and is far below the OECD average, leaving 830,000 JobSeeker recipients at risk

2 **The low level of JobSeeker is correlated with financial stress of families, poorer mental and physical health and worse childhood development outcomes**

3 Every $100 invested in an increased JobSeeker payment delivers a $24 social return. Further, the efficiency savings from health and childhood development improvements far outweigh even the most generous estimates of any potential reduction in job search intensity

4 Methodological appendix

Leading econometric studies estimate the effect of low payments in four areas: physical health, mental health, childhood development, and economic costs

Exhibit 6: Critical areas impacted by low incomes or unemployment benefit payments identified in a scan of international and domestic literature

Physical health

- Low-income households spend 40-59% less than higher-income households in absolute terms (but a greater share of their relative incomes) on medicines and health practitioner visits, despite being more likely to have a health condition.[1]
- For every $1 increase in income, there is a $0.20 increase in spending on health practitioners.[1]
- One in four Australian adults with select physical health conditions were avoiding care due to the cost.[2]
- In US studies, fewer primary healthcare visits are associated with more Emergency Department (ED) visits, more hospitalisations, and higher costs.[3]

Mental health

- Financial strain is correlated with more depressive symptoms, greater loneliness, and poorer self-reported physical health, mental health, and sleep.[4]
- $150 increases in JobSeeker payments during the pandemic resulted in financial stress declining by 0.03 points (out of five) and mental stress declining by 0.01 points.[5]
- Studies in Poland and Canada found psychological distress and depression increase inpatient costs (+22%) and outpatient costs (+8.9%).[6]
- In Canada, unemployment benefits reduce the probability of reporting poor self-rated health among the unemployed by up to 4.9%, with effects highest for low-income individuals.[7]

Childhood development

- A 1 standard deviation increase in family income lifts children's literacy and mathematics scores by 0.24-0.29 standard deviations. [8]
- Test scores at ages 5-6 are significantly correlated with educational attainment measured at age 18 or later.[9]
- For every 1% increase in total household expenditure, spending on preschool and primary education rises by approximately 1.45%.[10]
- Poverty (retrospectively assessed) is associated with a 1.9 times increase in the risk of any child maltreatment with 27% of all child maltreatment jointly attributable to economic factors.[11]

Broader economic impacts

- A meta-analysis of 54 studies published as an NBER Working Paper in 2024, found that after accounting for publication bias and study characteristics, a typical replacement rate duration elasticity is 0.36. Studies in countries with higher replacement rates have higher elasticities. In US studies, a 1% increase extends unemployment duration by 0.36% from a baseline replacement rate of 43.5%. In studies across OECD countries, it's higher at 0.55% from a 62% replacement rate baseline.[12]
- A study of welfare cuts for refugees in Denmark found a relationship between benefit levels and subsistence crime. Adult women increased grocery theft and teens faced increases in conviction probabilities for violent and property crimes.[13]

1 Best & Tuncay (2022). 2 Callander et al. (2019). 3 Rose et al. (2018). 4 Guan et al. (2022). 5 Botha et al. (2022). 6 Grabe et al. (2009). 7 Shahidi et al. (2019). 8 Khanam & Nghiem (2016). 9 Bernal & Keane (2011). 10 Jääskelä & Windsor (2011). 11 Doidge et al. (2017). 12 Cohen & Ganong (2024). 13 Dustmann et al. (2024a); Dustmann et al. (2024b).
Source: Mandala analysis.

Current JobSeeker rates make good nutrition, medicines and healthcare unaffordable, worsening physical health

JobSeekers struggle to make ends meet financially, with one in five reporting going without meals because of financial pressures in 2022. This prevalence is significantly higher than the broader population, for whom only one in twenty-five reported the same.

The low rate of JobSeeker forces people to rely on their family and friends for financial help and for informal care. Analysing HILDA Survey data, 36% of JobSeekers asked for financial help from friends or family in 2022.

JobSeekers report not being able to afford to go the doctor or to fill their prescriptions because of financial shortages. This is despite JobSeekers having more complex health situations to manage.

Of the 42% of JobSeekers assessed as having partial capacity to work; 42% have a psychological or psychiatric illness as their first listed medical condition (147,000, 18% of all JobSeekers); 31% have a musculo-skeletal diagnosis as their first-listed medical condition (108,000, 13% of all JobSeekers).

Exhibit 7: The low rate of JobSeeker may adversely affect recipients' physical health

% of JobSeeker recipients vs non-recipients aged 22-66, 2022

Poorer nutrition and food insecurity	21% of JobSeekers went without meals due to financial constraints, 5x more than non-recipients (4%).[1]
Inability to afford medicines or doctors	75% of working-age income support recipients could not access healthcare and medicine because they couldn't afford it.[2]
Worsening physical health	8 in 10 people said receiving income support negatively affected their physical health.[2]
Partial capacity to work	42% of JobSeekers (350,000) were assessed as having partial capacity to work, that is under 30 hours a week.[3]
Elevated risk of homelessness	1 in 10 people on working-age payments access homelessness services per year.[4]

1 JobSeeker status was determined by receiving JobSeeker for one week or more in the last twelve months (n= 571). HILDA Survey Wave 22 using population weights. 2 ACOSS (2024), n=760; 3 DSS (2024). 4 Taylor Fry (2021) *Pathways to Homelessness.* Source: Mandala analysis.

The high financial stress faced by JobSeekers correlates with poor mental health and high rates of suicide

Depression affects JobSeeker recipients at much higher rates than other Australians. In 2021, 18% of recipients reported feeling depressed all or most of the time – three times the rate of non-recipients (6%). These rates have stayed steady since before the pandemic.[1]

Poor mental health makes it harder to find and keep work. The Productivity Commission found mental health issues cost Australia over $12 billion annually through:

- Lower workforce participation
- More sick days
- Reduced productivity at work.[2]

But the relationship works both ways. Research shows that improving someone's chances of finding work also improves their mental health. Raising job search optimism by 10% boosts mental health as much as a $60,000 income increase.[3]

This suggests that supporting JobSeeker recipients' mental health could help them return to work faster, while finding work would further improve their mental wellbeing.

1 Mandala analysis of HILDA Waves 21 and 19.
2 Productivity Commission (2020) *Mental Health.*
3 Auer and La Cava (2023) *The mental health of Job Seekers.*

Exhibit 8: The low rate of JobSeeker may adversely affect recipients' mental health

% of JobSeeker recipients aged 22-66, 2022

Higher financial stress	JobSeekers are 5x more likely to be experiencing three or more measures of financial stress (26% vs 5% of non-recipients).[1]
Poor mental health outcomes	Almost one in two (45%) of JobSeekers had high or very high Kessler 10 scores, indicating high to severe depression or anxiety.[2]
Less access to psychologists	Only 26% of JobSeekers with a mental health treatment plan accessed allied health psychological treatment, compared to 34% of non-recipients.[3]
Lower workforce participation	People with mental health disorders have lower employment rates (62% vs 80% without disorders) and higher rates of being out of the labour force (32% vs 17%).[4]
Higher suicide rates	The highest numbers of suicides for those aged 22-45 years are JobSeeker Payment support recipients.[5]

Note: The Kessler-10 (K10) is a 10-item questionnaire measuring psychological distress based on questions about anxiety and depressive symptoms. A score >22 indicates high likelihood of having a mental health disorder.
1 HILDA Survey Wave 22; Mandala analysis. 2 Calculated from HILDA Survey Wave 21. 3 Calculated from PLIDA (2022). 3. Productivity Commission (2020). 4 Brisbane et al. (2022) based on ABS 2017-18. 5 AIHW (2024) *Deaths by suicide among Centrelink income support recipients* – Note this study is not causal – see page 35 for discussion.

Family stress and constrained resources to spend on education can inhibit child development outcomes

International evidence shows increases in income are associated with improvements in children's cognitive, social, and health outcomes. A systematic review of randomised control trials (RCTs), quasi-experimental studies, and observation studies using fixed effect longitudinal studies showed income positively impacted child outcomes in 63% of studies.[1]

An Australian study by Khanam and Nghiem (2016) examined family income effects on children's cognitive development. Using dynamic panel data, the study finds that family income is significantly associated with children's cognitive skills, as well as parents' education, child's birth weight, and number of books at home.[2]

A 2024 study examined the effects of a reduction of welfare benefit for adult refugees who received residency in Denmark, which reduced their disposable income by 30% on average over the first five years. It found that children exposed to the welfare cut during preschool and school-age obtained lower GPAs, had reduced well-being and overall education levels, and suffered lower employment and earnings as adults.[3]

1 Cooper and Stewart (2020). See Tables 5, 6, 7.
2 Khanam & Nghiem (2016).
3 Dustmann et al. (2024).

Exhibit 9: The low rate of JobSeeker may adversely affect childhood development

Effect sizes from the literature

Lower ability to spend on preschool	For every 1% increase in total household expenditure, spending on preschool and primary education rises by approximately 1.45%.[3]
Income is correlated with school performance	High quality US studies found a $1,000 increase in annual income is associated with a 10% improvement in school performance in the US.[4]
Income is correlated with emotional development	A study in Canada found a $1,000 increase in annual income was related to a 10% effect size for reductions in anxiety and physical aggression for children[5]

4 Jääskelä & Windsor, (2011). See Appendix A. Results are for 2009/2010. 5 Gennetian and Miller (2002). 6 Milligan and Stabile (2011). Source: Mandala analysis.

Welfare reductions aimed at incentivising labour market participation generated a negative return of -$12,000

Between 2002 and 2012, welfare for refugees granted residency in Denmark was reduced by 40% under the objective of boosting labour participation. Despite initial positive effects on adult employment, these gains were vastly outweighed by the long-term detrimental consequences on children. Observing a 16-year time horizon, the reform led to an estimated net loss of US$12,000 per family as:

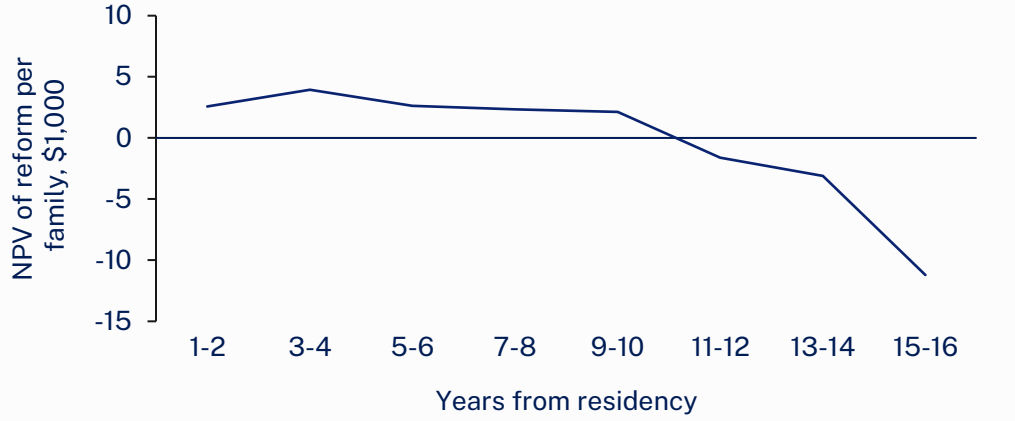
- Preschool attendance dropped, hindering early childhood development and integration.
- Children's educational outcomes declined, with lower GPAs and reduced overall educational attainment.
- Employment rates and earnings for affected children decreased as they entered adulthood.
- Crime rates among teenagers doubled, with higher rates of both property and violent offences for 14-18 year olds.

These long-term negative effects on children's outcomes far outweighed the short-term gains from increased adult labour force participation. The study underscores the importance of considering the comprehensive and long-term impacts of welfare reforms, particularly on vulnerable populations like refugee families

Exhibit 10: Unintended consequences of lowered welfare for refugees in Denmark

Net-returns of reform, adults' and children's earnings and crime, US$1,000, by years since residency

Cumulative returns of reform ($1,000) based on reform effects on earnings and crime



- The charts track this pattern: minor early employment gains were erased by rising social costs and poorer outcomes for children reaching adulthood. The cumulative cost (bottom chart) grew steadily negative.
- These findings are particularly relevant for Australia's uniquely targeted welfare system. Unlike Denmark, which cut benefits to match OECD averages, Australia already has the second-lowest replacement rate. This suggests reforms focused solely on work incentives could risk even greater intergenerational damage in our low-payment environment.

Source: Dustmann et al. (2024) *Unintended consequences of welfare cuts on children and adolescents;* Mandala analysis.

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4 Methodological appendix

Our analysis focusses on the microeconomic benefits of increasing the JobSeeker rate for a 20,000-person representative cohort

OUTLINE OF THE RESEARCH QUESTION AND PREVIOUS STUDIES

WHAT ARE THE IMPACTS OF INCREASING THE JOBSKEER PAYMENT?

CATEGORY		THIS STUDY
MICROECONOMIC IMPACTS	GOVERNMENT SAVINGS	Our analysis compares the **efficiency benefits** of increasing the JobSeeker with potential **efficiency costs.** It quantifies the microeconomic benefits of raising JobSeeker payments by tracking mental health, physical health and child development outcomes for 20,000 people over 10 years.
	BENEFITS TO INDIVIDUALS	
	BENEFITS TO SOCIETY	

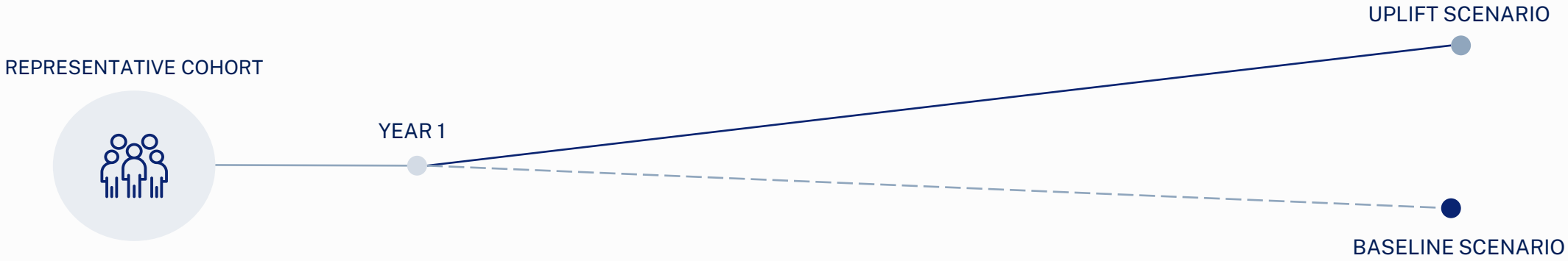
Not in scope

CATEGORY		PREVIOUS STUDIES AND THEIR FINDINGS
MACROECONOMIC IMPACTS	CONSUMPTION	Deloitte Access Economics (2018) observed the initial expenditure will create a dollar for dollar increase in the size of the economy and create 12,000 jobs.[1]
	TRANSFERS BETWEEN HOUSEHOLDS	Phillips and Webster (2022) observed that a high increase would reduce the poverty rate for JobSeekers from over 90% to 43%.[2]
	CHANGES TO GOVERNMENT BUDGET	Phillips and Webster (2022) observed that increases would require changes to taxes and concessions to finance, which would primarily cost high-income households, who have a greater capacity to absorb costs without increasing financial strain or poverty.[2]

1 Deloitte Access Economics (2018), *Analysis of the impact of raising benefit rates.*
2 Phillips & Webster (2022), *A Fairer Tax and Welfare System for Australia.*
Source: Mandala analysis.

The increase to JobSeeker is modelled using a microsimulation, which simulates the lifepaths and interactions of a 20,000-person representative cohort

THE MICROSIMULATION



A 20,000-person cohort is modelled based on the 142,000 that flow onto JobSeeker from 1 January to 31 March 2022:

- 48% have a spell that lasts for 3 months or less; 27% for 3-12 months
- 14% for 1-2 years
- 12% for 2+ years[2]

ECONOMIC FACTORS	HEALTH FACTORS	CHILDHOOD DEVELOPMENT FACTORS
▪ Labour force status ▪ JobSeeker status ▪ Time on JobSeeker ▪ Income ▪ Financial stress	▪ Health score ▪ Psychological distress (as measured by Kessler 10) ▪ GP visits ▪ Hospitalisations ▪ Quality Adjusted Life Years	▪ Year 9 NAPLAN scores ▪ Year 12 graduation

The representative cohort is modelled year by year in the microsimulation using a series of regressions to model every individual's economic, health and childhood development factors. These regressions have been created using Australian longitudinal datasets segmented for low-income Australians (under $50,000 annual income).

We model a 32.4% increase in the rate of JobSeeker to be equivalent to 90% of the Age Pension (which offers $1,144 per fortnight for singles including supplements). This is equivalent to an uplift to the single rate for JobSeekers (received by the majority of the cohort) from $389 to $515 per week.

1 Technical appendix slides contain further detail on the approach to modelling each outcome. 2 The duration of spells was observed in DOMINO data for the cohort until June 2024.

The outcome variables modelled in the microsimulation are used to quantify the benefits of raising JobSeeker to government, individuals, and broader society

TABLE OF BENEFITS

CATEGORY	GOVERNMENT SAVINGS	BENEFITS TO INDIVIDUALS	BENEFITS TO SOCIETY
PHYSICAL HEALTH	▪ GP visits ▪ Hospitalisations		
MENTAL HEALTH	▪ Mental health related healthcare ▪ Mental health related services (housing, justice) ▪ Increased tax from higher mental health-related productivity[1]	▪ Increased earnings ▪ Quality-Adjusted Life Years (QALYs) ▪ Out of pocket costs	▪ Insurer costs ▪ Lives lost due to suicide ▪ Informal care provided by friends and family ▪ Increased productivity gains from improved mental health[1]
CHILDHOOD DEVELOPMENT FACTORS	▪ Children's lifetime social security system use	▪ Children's increased earnings	▪ Avoided childhood poverty Disability-Adjusted Life Years (DALYs)
BROADER ECONOMIC FACTORS	▪ Reduced adult justice system interaction costs		▪ Avoided adolescent justice interactions

1 The productivity improvements are derived from the mental health outcomes observed among those who return to work in both scenarios – which are improved in the shock scenario - resulting in less presenteeism and absenteeism.
Source: Mandala analysis

For the representative cohort of 20,000, an increase to JobSeeker represents a social return of 24% to government, individuals and society

Exhibit 11: Benefit analysis for the 20,000-person cohort

	INCREMENTAL BENEFIT CATEGORY, $AU, NPV, 2025 to 2034	LOW	MEDIUM	HIGH
GOVERNMENT SAVINGS	AVOIDED HOSPITALISATIONS	$0.7m	$0.8m	$0.9m
	AVOIDED GP VISIT REBATES	$0.3m	$0.4m	$0.4m
	AVOIDED MENTAL HEALTH CARE COSTS	$1.7m	$1.9m	$2.2m
	AVOIDED MENTAL HEALTH RELATED SERVICES COSTS[1]	$0.7m	$0.8m	$0.7m
	MENTAL HEALTH-RELATED PRODUCTIVITY GAINS TO GOVT TAX REVENUE	$4.5m	$5.1m	$6.0m
	AVOIDED JUSTICE SYSTEM INTERACTION COSTS	$6.3m	$7.2m	$8.7m
	LOWER CHILD LIFETIME SOCIAL SECURITY SYSTEM USE	$0.5m	$0.5m	$0.5m
	TOTAL	**$14.7m**	**$16.7m**	**$19.4m**
BENEFITS TO INDIVIDUALS	INCREASED EARNINGS	$8.9m	$10.1m	$12.1m
	MENTAL HEALTH-RELATED QUALITY ADJUSTED LIFE YEARS	$7.1m	$7.8m	$8.9m
	AVOIDED OUT OF POCKET MENTAL HEALTH COSTS	$0.1m	$0.1m	$0.2m
	TOTAL	**$16.1m**	**$18.0m**	**$21.2m**
BENEFITS TO SOCIETY	MENTAL-HEALTH RELATED PRODUCTIVITY GAINS TO GDP	$19.0m	$21.3m	$25.0m
	AVOIDED LIVES LOST DUE TO SUICIDE	$4.3m	$4.7m	$5.4m
	AVOIDED CHILDHOOD POVERTY-RELATED DISABILITY ADJUSTED LIFE YEARS	$4.5m	$4.9m	$5.6m
	CHILDRENS' INCREASED EARNINGS	$1.3m	$1.6m	$2.2m
	AVOIDED ADOLESCENT JUSTICE SYSTEM INTERACTION COSTS	$1.9m	$2.0m	$2.2m
	INFORMAL CARE PROVIDED BY FAMILY AND FRIENDS	$2.6m	$2.9m	$3.4m
	AVOIDED INSURER MENTAL HEALTH COSTS	$0.2m	$0.2m	$0.2m
	TOTAL	**$33.8m**	**$37.6m**	**$44.0m**
	TOTAL	**$64.6m**	**$72.3m**	**$84.6m**

Overall, the increase to JobSeeker at least a 24% social return to government, individuals and society in the medium-case scenario for a 20,000-person representative cohort of payment recipients.

Increasing the JobSeeker Payment for this 20,000-person representative cohort would present a fiscal cost to government of $301 million in net present value terms. This represents a transfer from the Government's balance sheet to the balance sheet of households. Households spend this money in the economy. This generates an economic return (as shown in previous studies) as well as a $72.3 million (24%) social return for this 20,000-person cohort. We do not consider the macro-economic cost of raising taxation to fund the increase as this is out of scope.[2]

The 24% social return is delivered through three primary channels:

- Government savings: $16.7 million, equivalent to just under a quarter of the social benefits
- Benefits to individuals: $18.0 million, equivalent to a quarter of the social benefits
- Broader societal benefits: $37.6 million, equivalent to over half of the social benefits

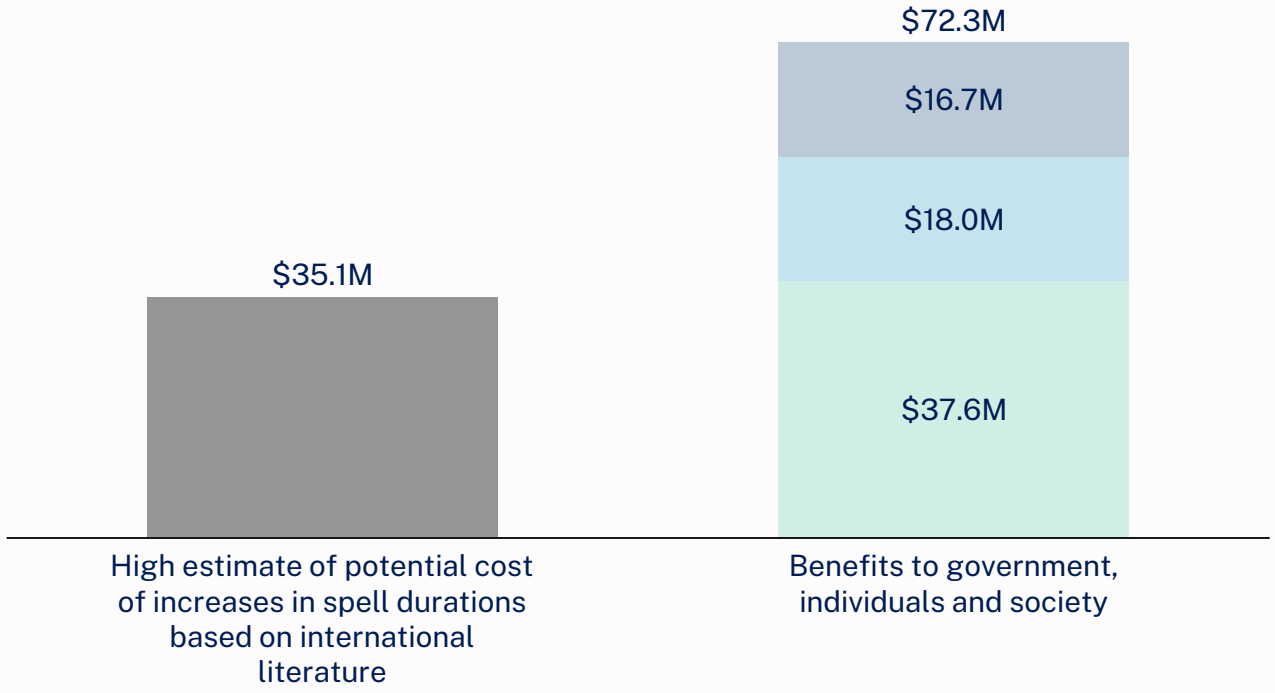
These projections are in net present value terms over a 10-year period for a cohort of 20,000 recipients.

1. Includes mental health-related housing, justice, employment services and psychosocial supports. 2 See Phillips & Webster (2022).
Low, medium and high scenarios represent discount rates of 10%, 7% and 3%.. See Appendix for detailed methodology. Source: Mandala analysis.

From an efficiency perspective, the benefits of this investment far outweigh the potential cost of increased job search durations

Exhibit 12: Potential costs versus benefits of an increase in JobSeeker to 90% of the Age Pension

$AU, Net present value, 2025-2034



Key findings

- Our analysis finds that the efficiency benefits of investing in JobSeeker for government, individuals and society far outweigh the potential efficiency costs.
- It is unlikely that increasing JobSeeker to 90% of the Age Pension would increase job search durations given the payment would remain significantly lower than the average wage. Even if job search durations increase, the cost would be far outweighed by the social return.
- The maximum potential cost expected in terms of increased job search durations on JobSeekers is $35.1 million. This estimate is based on a meta-analysis of 54 studies published as an NBER Working Paper this year. It found that after accounting for publication bias and study characteristics, a typical replacement rate duration elasticity is 0.36.[1]
- This meta-analysis finds that the elasticities observed for duration increases are higher in countries with higher replacement rates. As Australia's replacement rate is lower, and given strict means testing and job search obligations in Australia, it is likely that the elasticity of duration increases is lower in Australia.

Source: Elasticity of duration on benefits compared to a 1% increase in benefit generosity estimate from Cohen and Ganong (2024); Mandala analysis.

Almost a quarter of the social return from an increase in JobSeeker accrues to government

Overall, the government saves $16.7 million in cohort costs over the 10-year period across healthcare, justice and children's welfare use as well as additional government revenue through taxation. From a government perspective, there is a financial cost to increase JobSeeker ($301 million for this 20,000 cohort), but from a societal perspective the money goes into the economy and the cost represents a transfer between groups in the community.

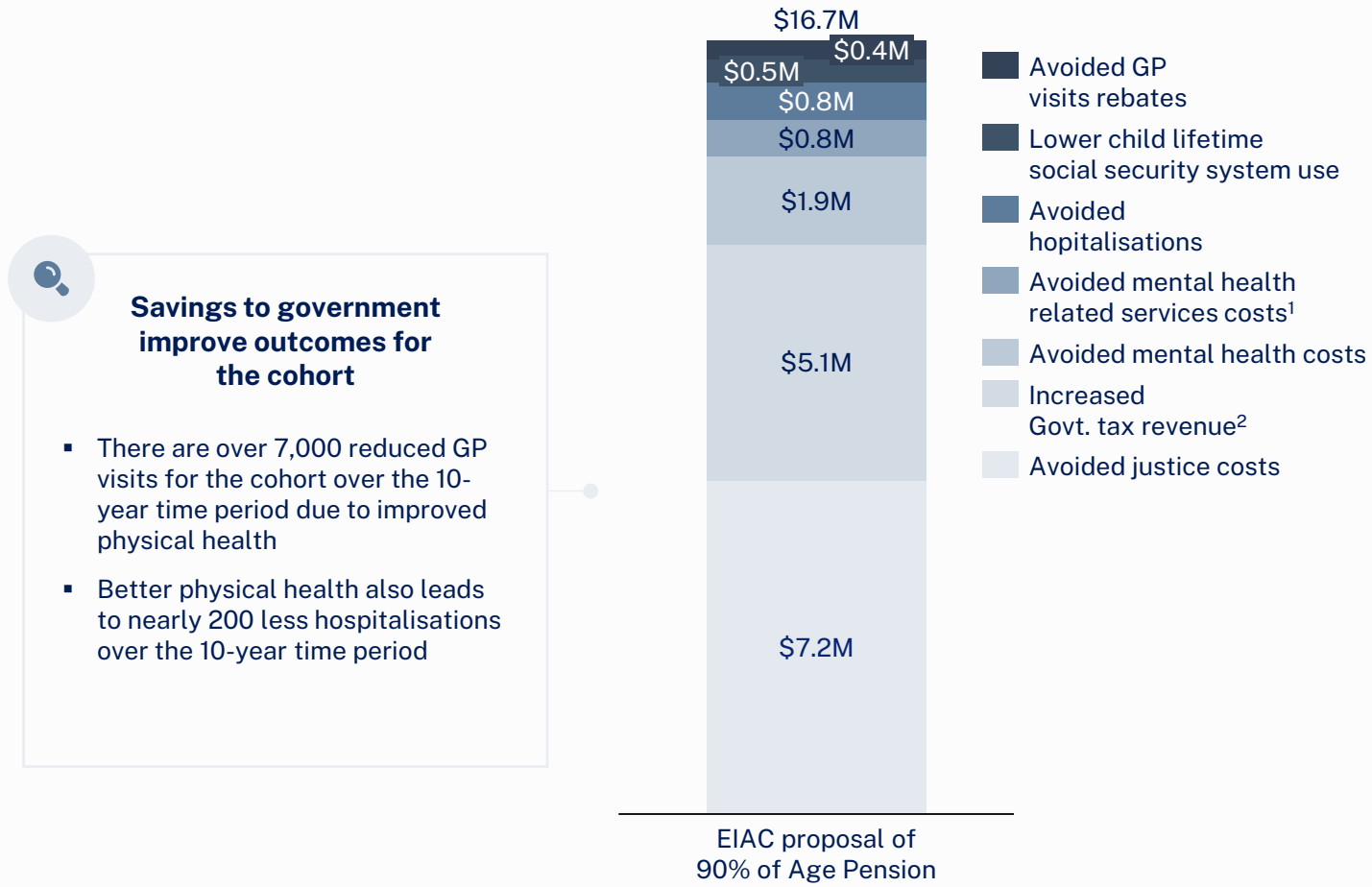
For JobSeekers, healthcare costs fall by 0.5%. This is driven by avoided mental health service usage. The higher payment reduces financial stress (with income elasticity of 0.21-0.29), which then reduces their psychological distress (by 0.675 points on a 4-point scale). This reduces mental health services costs and related service costs.[1]

For physical health, while people initially visit their GP more often when they can afford to (with income elasticity of 0.20-0.27), over time their improved health means fewer GP visits and they are less likely to be hospitalised (odds ratio of 0.99 for each point of health improvement).

The intergenerational effects of increasing JobSeeker improve children's outcomes. Higher family income lifts NAPLAN scores by 17-21 points, and higher scores make students more likely to complete Year 12 (odds ratio of 1.003 per point). Improved education reduces the likelihood of these children needing welfare later in life.

Exhibit 13: Total Government savings from increasing JobSeeker for representative cohort

$AUD, NPV @ 7% real discount rate, 2025 to 2034



Savings to government improve outcomes for the cohort

- There are over 7,000 reduced GP visits for the cohort over the 10-year time period due to improved physical health
- Better physical health also leads to nearly 200 less hospitalisations over the 10-year time period

Note: All modelling uses DSS DOMINO administrative data, HILDA survey data (Waves 1-22), LSAC survey data (Waves 1 to 9C) and LSAY survey data (year 15 cohort).
1 Includes mental health-related housing, justice, employment services and psychosocial supports.
2 Improvements to productivity are measured through decreased absenteeism and increased presenteeism which increase Government tax revenue (Appendix B: Slide 57). Source: Mandala analysis.

An additional quarter of the social return from an increase to the JobSeeker Payment accrues to individuals

The increase to JobSeeker provides $18.0 million in direct cohort benefits to individuals through improved mental health and earnings, as well as reduced out of pocket mental health costs for the cohort.

The increase to JobSeeker is associated with a 0.1% increase in the earnings of individuals in the cohort due to improved mental health, resulting in faster return to work. Each point increase in the psychological distress reduces the likelihood of returning to work in the next year (0.86 odds ratio). Lowering the psychological distress of the cohort results in more people moving off JobSeeker.

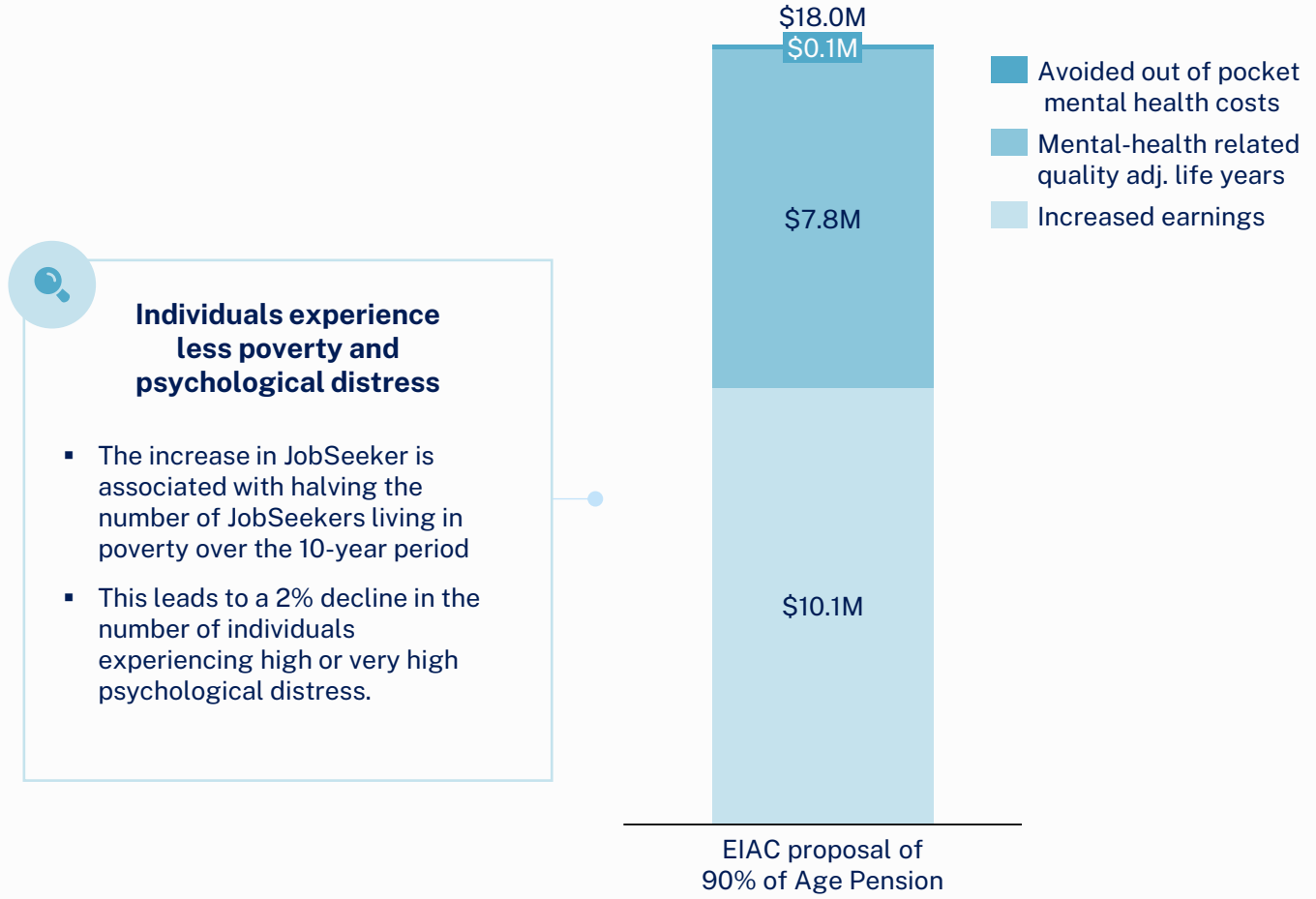
Improved mental health of the cohort leads to better quality of life outcomes for the cohort. The increase to the JobSeeker payment is associated with an 0.1% increase in the number of quality-adjusted life years. When psychological distress scores improve by one point (decreases by one point) a person gains 0.084 quality-adjusted life years. During the 10-year time period, the 20,000 person cohort experiences an extra 127 quality-adjusted life years in total; where each quality-adjusted life year is valued at $79,000.[1]

Additionally, there is a 0.5% decrease in the out of pocket mental health costs that individuals pay thanks to improved mental health.

1 $79,000 per one QALY in 2023 dollars, scaled for inflation from Huang et al.'s (2018) *Life satisfaction, QALYs, and the monetary value of health* estimate that individual's willingness to pay for one QALY is approximately A$42,000-A$67,000.

Exhibit 14: Total benefits to individuals from increasing JobSeeker for representative cohort

$AUD, NPV @ 7% real discount rate, 2025 to 2034



Individuals experience less poverty and psychological distress

- The increase in JobSeeker is associated with halving the number of JobSeekers living in poverty over the 10-year period
- This leads to a 2% decline in the number of individuals experiencing high or very high psychological distress.

Note All modelling uses DSS DOMINO administrative data, HILDA survey data (Waves 1-22)
Source: Mandala analysis.

The remaining half of the social return from an increase to JobSeeker accrues to broader society

The increase to JobSeeker leads to $37.6 million in broader benefits to society over 10-years for the 20,000-person representative cohort, including additional benefits to the family and friends of the cohort as well as additional productivity gains to GDP.

Most of these benefits are due to improved productivity. The increased payment is associated with better mental health and lower psychological distress. Better mental health results in improved work performance for those who return to work, with the individuals taking fewer sick days and being more productive.[1]

The improved mental health of the cohort also reduces the number of suicides, which adds $4.7 million in benefits through the avoided lives lost.[2]

The increase to JobSeeker is associated with a reduction in childhood poverty. Increasing the number of children who never experience poverty results in $4.9 million benefits through avoided losses of disability adjusted life years for the children of the cohort.[3]

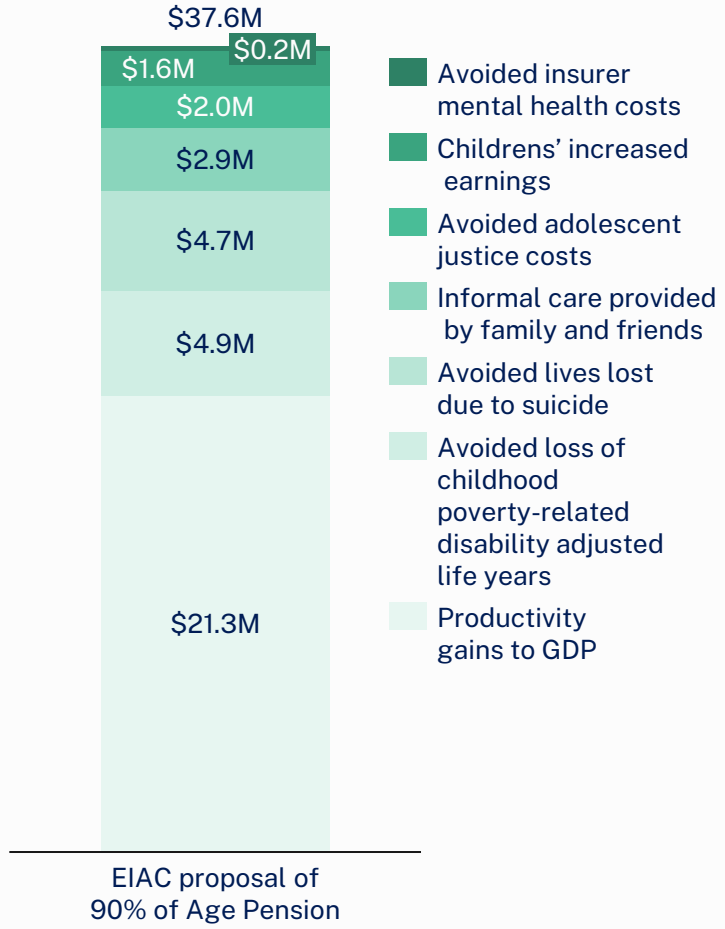
1 Improvements to productivity are measured through decreased absenteeism and increased presenteeism (Appendix B: Slide 57)
2 Suicides are modelled using the levels of psychological distress within the cohort (Appendix B: Slide 83 to 86)
3 Avoided childhood poverty is calculated using the incomes of the cohort (Appendix B: Slide 87)

Exhibit 15: Total broader benefits to society from increasing JobSeeker for representative cohort

$AUD, NPV @ 7% real discount rate, 2025 to 2034

Families, including children, benefit from increasing JobSeeker

- Suicides are reduced by 1% over the 10-year period due to the improvements in mental health associated with the increase in the JobSeeker Payment.
- The increase is also associated with a 25% increase in the number of children who never experience childhood poverty.



Note All modelling uses DSS DOMINO administrative data, HILDA survey data (Waves 1-22)
Source: Mandala analysis

Estimating social returns was highly challenging due to a lack of Australian evidence and data in the available literature

LIMITATIONS AND CHALLENGES OF THE ANALYSIS

CAUSALITY AND ASSOCIATIONS

- Our report draws on the literature that identifies causal pathways where possible, but many relationships could not be created using causal techniques
- Instead, we have created regressions that follow the causal pathways in the literature with the aim to model the possible effect sizes of the changes to income using a low-income population
- It is important to note that we do not use these regressions to imply causality but to estimate these effect sizes for our microsimulation
- There is a significant lack of literature in Australia exploring the relationships between income (or benefit levels or poverty) and key social, health and economic outcome variables

NON-QUANTIFIED BENEFITS

- It is likely that our analysis significantly understate the benefits, as it excludes many difficult-to-quantify benefits, including but not limited to:
  - Dental access and outcomes
  - Ability to afford medicine
  - Relationships between accessing medicine and physical health
  - Housing and homeless benefits
  - Out of home care benefits
  - Reducing poverty and hence the social and emotional costs of poverty
  - Reducing educational support costs related to children's mental health outcomes
- Advice from subject matter experts indicates the unquantified benefits are substantial.

FIXED EFFECT VS. EXPERIMENTAL STUDIES

- Modelling in this report relies on results from generalized linear models (GLMs) to derive benefits of the increase instead of experimental studies (e.g. randomized controlled trials)
- We designed our own GLMs instead of using experimental studies as many of these studies did not provide income elasticities at the granularity required to model the benefits (e.g. modelling between income bands)
- This means that the benefits modelled in this analysis are likely conservative,[1] for example the reduction in the number of hospitalisations

MACROECONOMIC EFFECTS

- This report does not model the macroeconomic effects of recipients additional spending, household transfers to fund the increase or changes to government budgets as it is beyond our scope
- Previous research conducted by Deloitte Access Economics, and Phillips and Webster has examined the macroeconomic impacts of an increase to JobSeeker
- Additional analysis could quantify the social welfare effects on high-income households who would need to fund the increase to JobSeeker

1 Cooper and Stewart (2021), while identifying the effects of household income on childhood development outcomes, found that effects tend to be larger in experimental and quasi-experimental studies than in fixed effect approaches. Source: Mandala analysis.

MANDALA

Appendix A: Review of academic literature

APPENDIX A

Research shows that low incomes are correlated with financial stress, poorer health, and poorer childhood outcomes

This study explores relevant international and Australian research on the evidence base on the likely costs and social benefits of raising the JobSeeker payment. Where possible, the study looks for evidence that controls for confounding variables – either through study design (e.g. randomised control trials), or through controlling for fixed effects in the analysis.

In this way, the impact of either a higher level of income for low-income individuals or an increase in unemployment benefit generosity on economic and social outcomes can be explored.

This study focusses on the outcomes across mental health by reducing financial stress, improving physical health through increased ability to afford nutritious food, medicine and visits to healthcare practitioners, improved childhood development through increased family spending on children and lower family stress, and behavioural effects including understanding the relationship between benefit levels and duration elasticities.

Exhibit 16: Relationships between unemployment benefit levels, or income, are explored for:

Literature review criteria[1]	
a **Recent**	We prioritise studies published within the last 10 years (2014-2024)[1]
b **Reliable**	A reliable academic article, research from a public institution, or research from a respected consultancy/thinktank
c **Prioritise Australia**	Australia's welfare system is unique. We prioritise studies using Australian data to ensure best validity
d **Focus on best international literature**	In the case of limited Australian literature, we defer to the best international research from peers

Key outcomes
2.1 **Mental health**
2.2 **Physical health**
2.3 **Childhood development**
2.4 **Behavioural effects**

1 Due to limited Australian research, we make a judgement on the relevancy of the study based on the data and methodology used. In some cases, papers published prior to 2014 are featured.
2 See appendix for all sources used. Source: Mandala analysis.

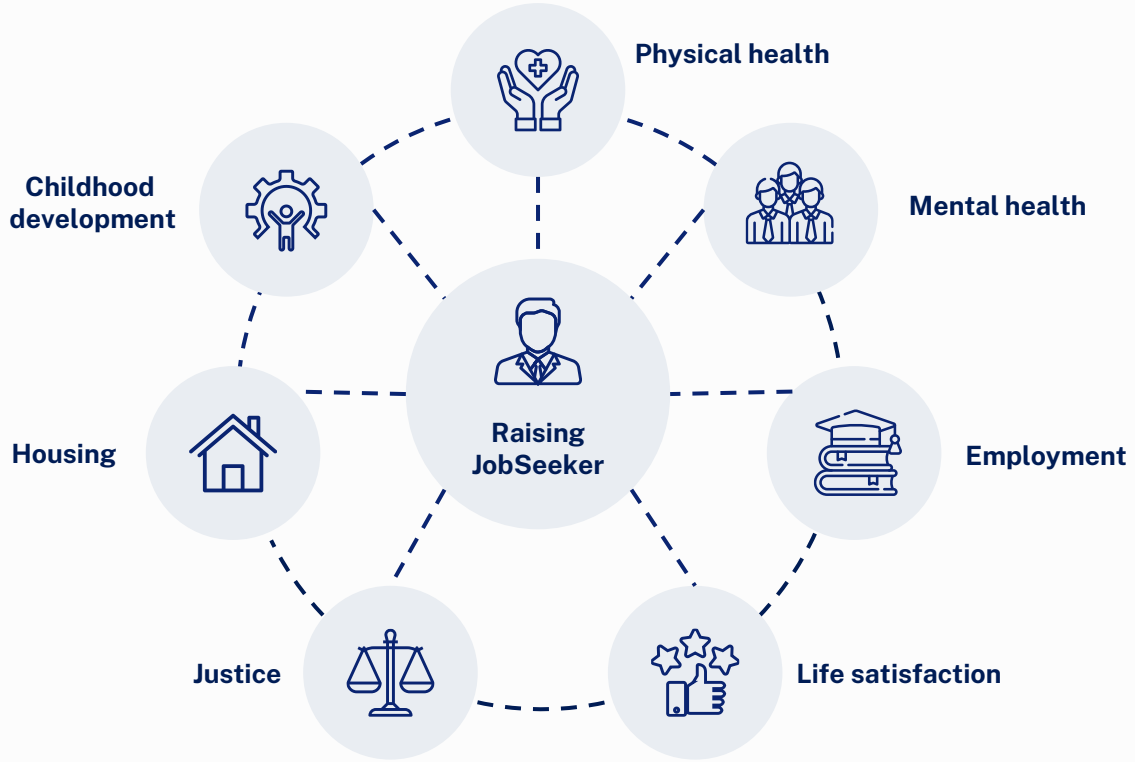
The social and economic benefits of raising income support payments are connected

Each aspect of a person's wellbeing is interconnected. Improvements in one social outcome are often caused by and in turn cause improvements in another outcome.

An increase in income support payment levels can drive economic and social benefits:

- Immediate effects: a rise in income has direct links to improvements in social outcomes, primarily via increased consumption and reduced financial strain. For example, higher incomes supports higher expenditure on healthcare, leading to direct improvements in health.
- Longer term effects: these social benefits have flow-on effects on other connected aspects of a person's economic and social wellbeing. For example, an improvement in health leads to greater capacity for employment, leading to ability to afford better housing, and so forth.

Exhibit 17: The interdependence of social benefits



- Each aspect of a person's wellbeing and social outcomes are interconnected. Improvements in one social outcome are often caused by and in turn cause improvements in another outcome.
- This study examines research into the relationship between income or unemployment benefits and socio-economic outcomes across mental and physical health, childhood development, and employment behaviours.

Source: Mandala analysis.

Financial stress increases psychological distress and depression; reducing financial stress can be a mediating factor on mental ill-health

Financial strain and hardship are unequivocally linked with increased psychological distress and illness.

Loss of income causes mental illness.[1] The causal relationship between poverty and mental health disproportionately affects the poor and may have lasting impacts on their economic well-being.[1]

Kiely et al. (2015) found a significant association between current financial hardship and increased risk of mental health problems.[2] Taylor et al. (2017), identified financial strain — particularly from housing costs and job security — as the primary predictor of psychological distress among parents in Western Sydney.[3] Economou et al. (2018) found financial hardship is a key risk factor in the development of major depression.[4]

Sareen et al. (2011) found a decrease in household income between two time points was associated with an increased risk of incident mood, anxiety, or substance use disorders (adjusted odds ratio, 1.30; 99% confidence interval, 1.06-1.60) in comparison with respondents with no change in income.[5]

Aranda and Lincoln (2011) found a relationship between financial strain and depressive symptoms in later life.[6]

The costs of mental ill-health to Australia are significant.

The Productivity Commission (2020) Inquiry into Mental Health in Australia conservatively estimated mental ill-health costs Australia over $200 billion each year, or $550m per day. This includes $16b in health-related costs, $12-39b in loss of participation and productivity costs, and $150b in costs related to disability and premature death. Australians with severe mental illness on average die 10 to 15 years earlier, usually as a result of physical comorbidities.[7] Other studies note the increase in likelihood of catastrophic health expenditure due to the comorbidity of mental health with chronic illnesses such as diabetes and heart disease.[1]

Reducing financial strain, such as through higher unemployment benefits, can be a mediating factor on mental distress and ill-health.

Chen et al.'s (2023) longitudinal study in the US of cross-state and time series variation in unemployment benefits between 2003-2013 found a one standard deviation ($1,000) increase in benefits was associated with a 5.1% improvement in self-reported mental health among the unemployed.[8]

In Australia, Butterworth et al. (2012) (n=8841) found a stronger relationship between financial hardship and 12-month depressive episodes than other socioeconomic factors. The findings suggest that addressing inequality in living conditions could be an effective way to minimise the burden of depression.[9]

Generous unemployment benefits are linked to better mental health and well-being among the unemployed, compared to countries with less generous benefits.[10]

Sources: 1. Ridley et al. (2020). 2. Kiely et al. (2015) 3. Taylor et al. (2017); 4. Economou et al (2018); Paleologou et al. (2019). 5. Sareen et al (2011). 6. Aranda and Lincoln (2011) 7. Productivity Commission (2020). 8. Chen et al. (2023). 9. Butterworth et al. (2012). 10. Kamerāde and Bennett (2017). Mandala analysis.

JobSeekers struggle to pay rent, heat their homes, and often rely on community organisations for help

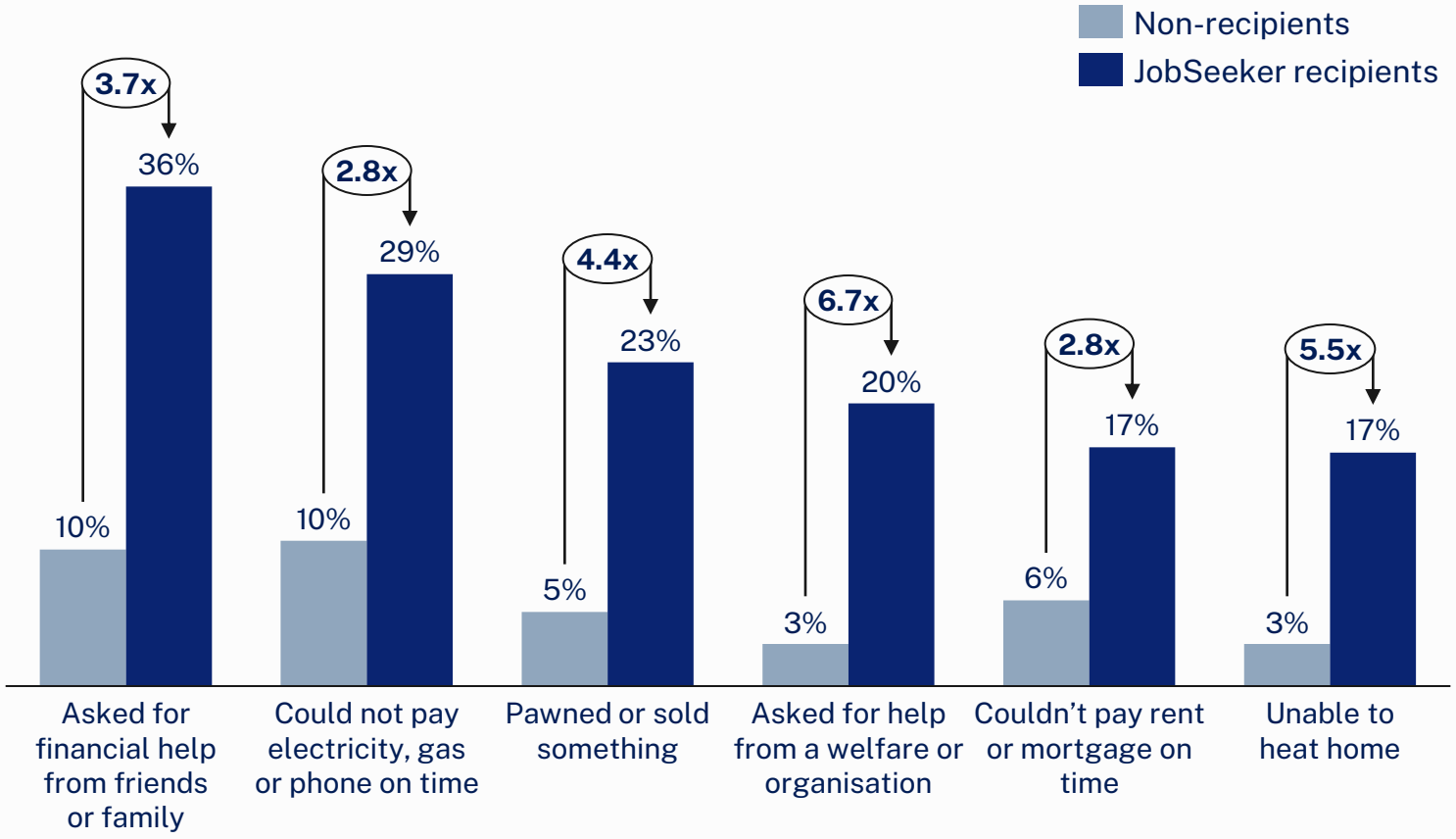
JobSeeker recipients experienced significantly higher rates of financial stress than non-recipients in Australia aged 22 to 66 across all measures.

For JobSeeker Payment recipients, the prevalence of experiencing at least one of the following stress measures since 1 January 2022 was significantly higher than non-recipients. For JobSeeker recipients in 2022:

- 36% asked for financial help from friends or family because of a shortage of money
- 29% could not pay their electricity, gas or phone bill on time because of a shortage of money
- 23% pawned or sold something because of a shortage of money
- 20% asked for help from a welfare or community organisation
- 17% couldn't pay their rent or mortgage on time because of a shortage of money
- 17% were unable to heat their home because of a shortage of money

Exhibit 18: Prevalence of experiencing the following because of a shortage of money

% of persons aged 22 to 66, 2022



JobSeeker status was determined by receiving JobSeeker for one week or more in the last twelve months (n obs = 571), variable: bnfnwsw.
Source: HILDA Survey Wave 22 using population weights; Mandala analysis.

Increases in JobSeeker reduce financial stress, improving mental health

Botha, Butterworth and Wilkins (2022) analysed unique nationally representative repeated cross-sectional data of 3,843 unemployed Australian adults over the period 6 April 2020 to 10 May 2021.

They found the Coronavirus Supplement payment significantly reduced reported financial stress, and lower financial stress was associated with lower mental distress.[1]

Financial strain is correlated with more depressive symptoms, greater loneliness, and poorer self-reported physical health, mental health, and sleep.[2]

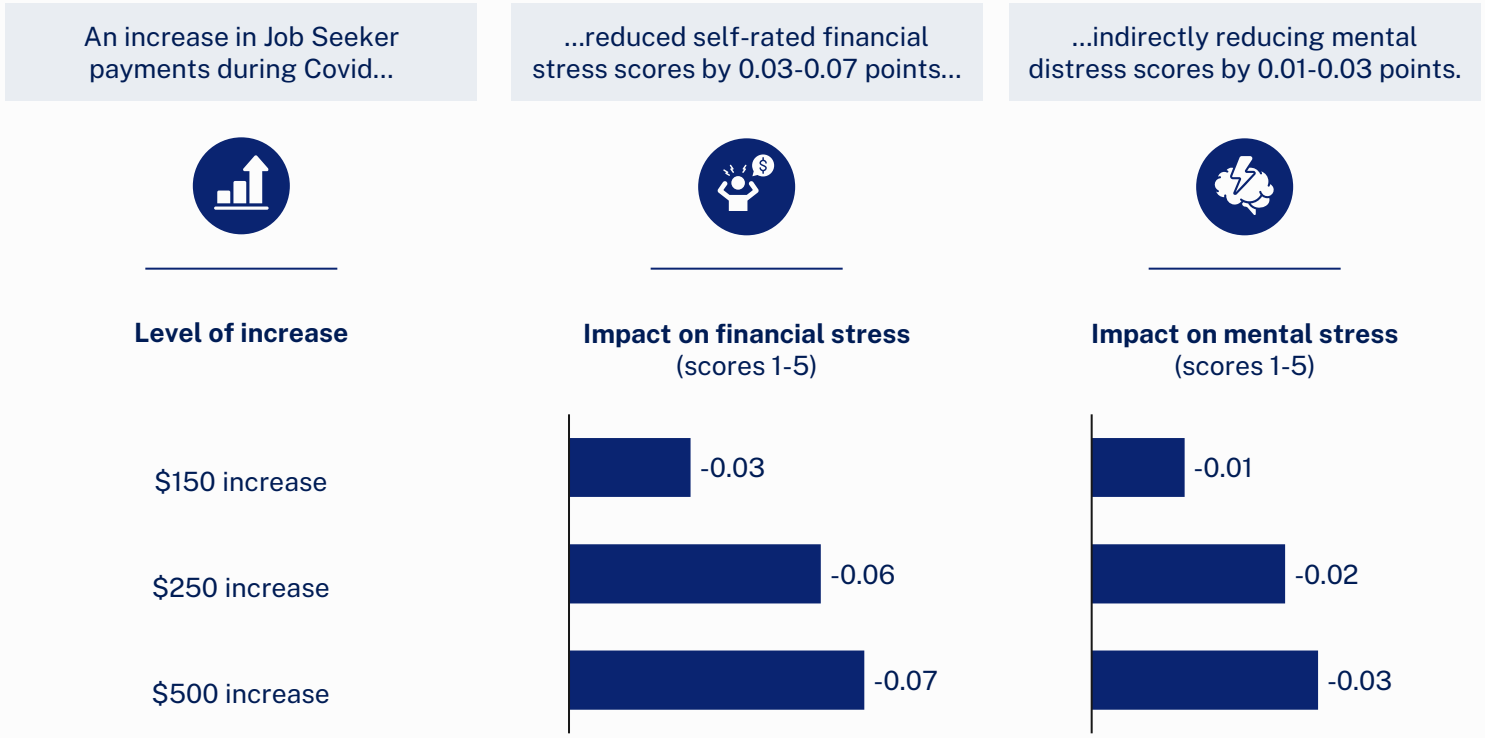
Zuelke et al. (2018) find unemployed persons receiving means-tested benefits constitute a risk group for depression that needs specific attention in the health care and social security system.[3]

Higher mental stress results in increased psychological distress and depression, which studies in Poland and Canada have shown increases inpatient costs (+22-24.1%) and outpatient costs (+8.9%).[4]

1. Botha, Butterworth and Wilkins (2022). 2. Guan et al. (2022); Butterworth et al. (2009); Sareen et al. (2008); Steptoe et al. (2020). 3. Zuelke et al. (2018). 4. Chiu et al. (2017); Grabe et al. (2009).

Exhibit 19: The impact of increases to JobSeeker during Covid-19 on the mental health of JobSeekers[5]

2022, standardised results



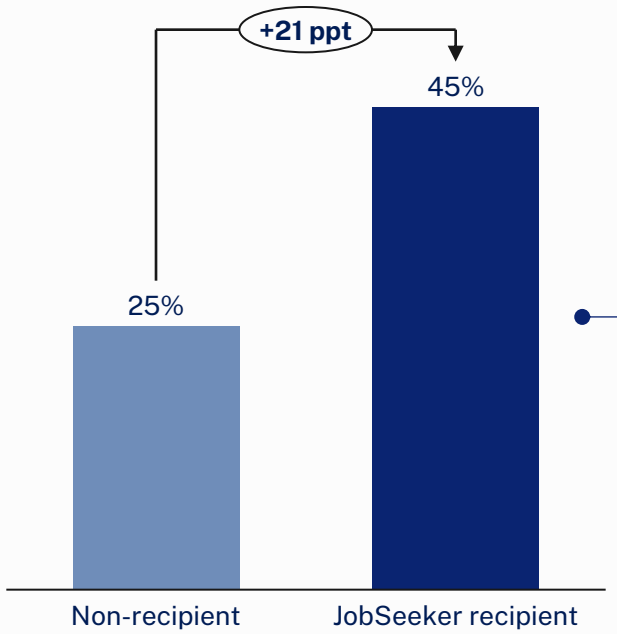
Our analysis of low-income households in HILDA demonstrated that a 1% increase in income is associated with a 0.3% reduction in the likelihood of being under financial stress and furthermore, that not being under financial stress increases psychological distress reduces by 0.675 points.

Source: Botha, Butterworth and Wilkins (2022) *Protecting mental health during periods of financial stress: Evidence from the Australian Coronavirus Supplement income support payment*, Table 3 & 5; HILDA Survey Wave 22 using population weights; Mandala analysis.

JobSeekers were almost twice as likely to be experiencing high to severe depression or anxiety...

Exhibit 20: Proportion of population experiencing a High or Very High psychological distress (Kessler 10 score greater than 22)

% of persons aged 22 to 66, 2021



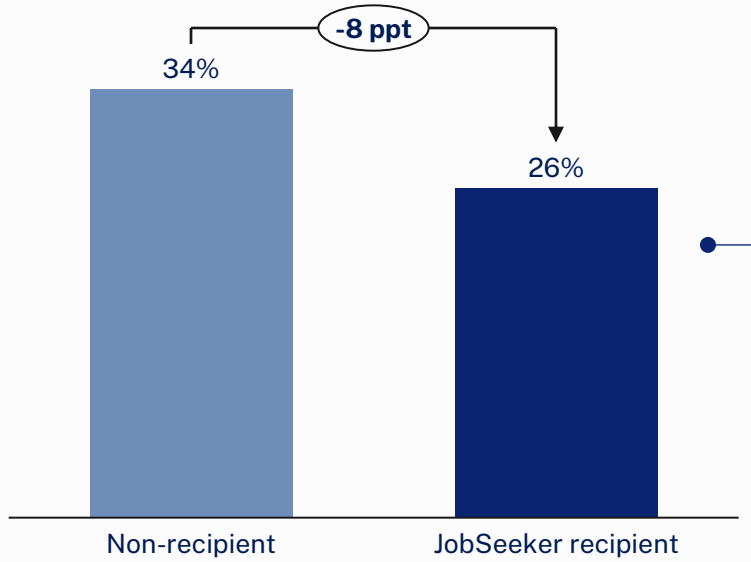
Almost one in two (45%) of JobSeeker recipients had a high or very high K10 score, indicating high to severe depression or anxiety.

JobSeeker status was determined by receiving JobSeeker for one week or more in the last twelve months (n obs = 571), Between 2019 and 2021, the prevalence of JobSeeker recipients experiencing Very high or High K10 scores declined slightly from 47% to 45%, while for non-JobSeeker recipients the prevalence rose from 20% to 25%.
Source: HILDA Survey Wave 21 using population weights; Mandala analysis.

... yet those with mental health treatment plans are less likely to access psychological treatment

Exhibit 21: Proportion of population with a mental health treatment plan who access allied health psychological services

% of persons aged 22 to 66, 2022



JobSeekers with a mental health treatment plan are less likely to access psychological treatment.

When people are not able to access care and support at the right time, this can lead to preventable psychological illness that becomes more severe and tend to be more costly to treat.[1]

1 The study population is the group of individuals that have a mental health treatment plan. 2 Productivity Commission (2020) *Mental Health Inquiry.*
Source: PLIDA, Mandala analysis

Lowering financial and psychological distress improves employment outcomes

Psychological distress worsens labour force outcomes.

Using Australian panel data from HILDA between 2002 to 2011 (n = 14,000), Frijters et al. (2014) tested the two-way causality between health and work. They used the panel structure and 'the death of a close friend in the last 3 years' as an instrumental variable to control for the endogeneity between employment status, wages and mental health.[1]

After these controls, Frijters et al. (2014) found a one-standard-deviation decline in mental health reduces employment by 30 percentage points.[1] Further investigations suggest that this effect is predominantly a supply rather than a demand-side response and is larger for older than young workers.[1]

Studies of the causal relationship between mental health and employment find diagnoses of psychiatric disorders and depression reduce the probability of employment by 13–26% across cohorts.[2]

Germinario et al (2022)'s approach estimated bounds that categorised as depressed decreases employment by 10% and earnings by 27%.[3] Examining different levels of adverse mental health, they found going from having no (little) to severe depressive symptoms reduces employment by 3–18% and earnings by 11–44%.[3]

Chatterji et al (2011) found having a psychiatric disorder in the past year is associated with reductions of 9 and 14 percentage points in the likelihood of current labour force participation and in the likelihood of employment among males, and 19 and 13 percentage point reductions in these outcomes respectively among females.[4]

Increasing income for disadvantaged groups, including through government interventions on tax or benefits, improves non-work to work transitions.

A large-scale randomised controlled trial of guaranteed income in Los Angeles over the past two years showed recipients of a guaranteed income support of US$1,000 per month were significantly more likely to secure full-time employment than to remain unemployed not looking for work, compared to control participants across the duration of the pilot.[5]

In Australia, Cai et al. (2008) examined the effect of the New Tax System reforms in 2000 on lone parents. The reforms reduced the effective marginal tax rates and eased budget constraints.[6] The study found non-work to work transition increased by an estimated 1.43 percentage points.[6] At the same time, a smaller disincentive effect for work to non-work transitions increased by an estimated 0.88 percentage points. This means on net, more people transitioned into work than out. Average hours worked per week increased by 0.43, from a base on 13.50 hours.[6]

Sources: 1. Frijters et al. (2014). 2. Alexandre and French (2001); Chatterji et al. (2007); Ettner et al. (1997). 3. Germinario et al. (2022) 4. Chatterji et al. (2011) 5. Kim et al. (2024). 6. Cai et al. (2008). Mandala analysis.

Improving mental health outcomes will improve productivity

Mental ill-health increases absenteeism, presenteeism and withdrawal from the labour market.

For example, depression typically disrupts sleep, leading to fatigue and concentration problems which trigger higher rates of absenteeism, lower labour supply, lower productivity, and thus lower earnings. Going from having no (little) to severe depressive symptoms reduces employment by 3–18% and earnings by 11–44%.[1]

An NBER Working Paper by Prinz et al. (2018) summarised the literature on the role of mental health in determining labour market outcomes in developed economies. They identified 11 studies with different methods that explore economic outcomes including labour force status, wages and productivity.[2] This included a 1998 randomised controlled trial that found strong evidence that when antidepressants reduce depressive symptoms, the subjective evaluation of work productivity improves.[3]

Banerjee et al. (2015) address the potential endogeneity of mental illness using Lewbel's (2012) approach that relies on heteroscedastic covariance restrictions. They find adverse effects on employment and labour force participation, fewer weeks worked and increased absenteeism are related to mental illness.[4]

Frijters et al. (2014) use 10 waves of HILDA panel data with an instrumental variable model that allows for individual-level fixed effects to control for time-invariant individual characteristics correlated with mental health and labour market outcomes. This method is applied to understand the two-way causality between mental health and work. They find evidence that a one-standard-deviation decline in mental health reduces employment by 30 percentage points.[5]

Jiménez-Solomon et al. (2024) used cross-lagged panel models with unit fixed effects and data from a five-wave representative panel (n = 3,103) of working-age (18–64) New York City adults. Yearly measures include individual earnings, family income (income-to-needs), and psychological distress; as well as examining effects by age, gender, education, and racial/ethnic identification. They found increases in psychological distress reduce next-year earnings (β= −0.03).[6]

The Productivity Commission's (2020) inquiry identify the loss of participation and productivity caused by the lower participation, absenteeism and presenteeism effects of poor mental health costs more than $12 billion annually to the Australian economy. The Inquiry found reforms to improve mental health increase the likelihood of employment and expected incomes, while also improving health-related quality of life. The Inquiry estimates that key reforms would create annual benefits of up to $1.3 billion per year via economic participation and productivity.[7]

Additionally, the evidence finds health shocks increase the burden of informal care on partners.[8]

Sources: 1. Germinario et al. (2022) 2. Prinz et al. (2018). 3. Berndt et al. (1998). 4. Banerjee et al. (2015). 5. Frijters et al. (2014). 6. Jiménez-Solomon et al. (2024). 7. Productivity Commission (2020). 8. Giaquinto et al. (2022); Mandala analysis.

JobSeeker recipients had the highest number of suicides among income support recipients

In the decade to 2021, 5,997 unemployment payment recipients died by suicide.

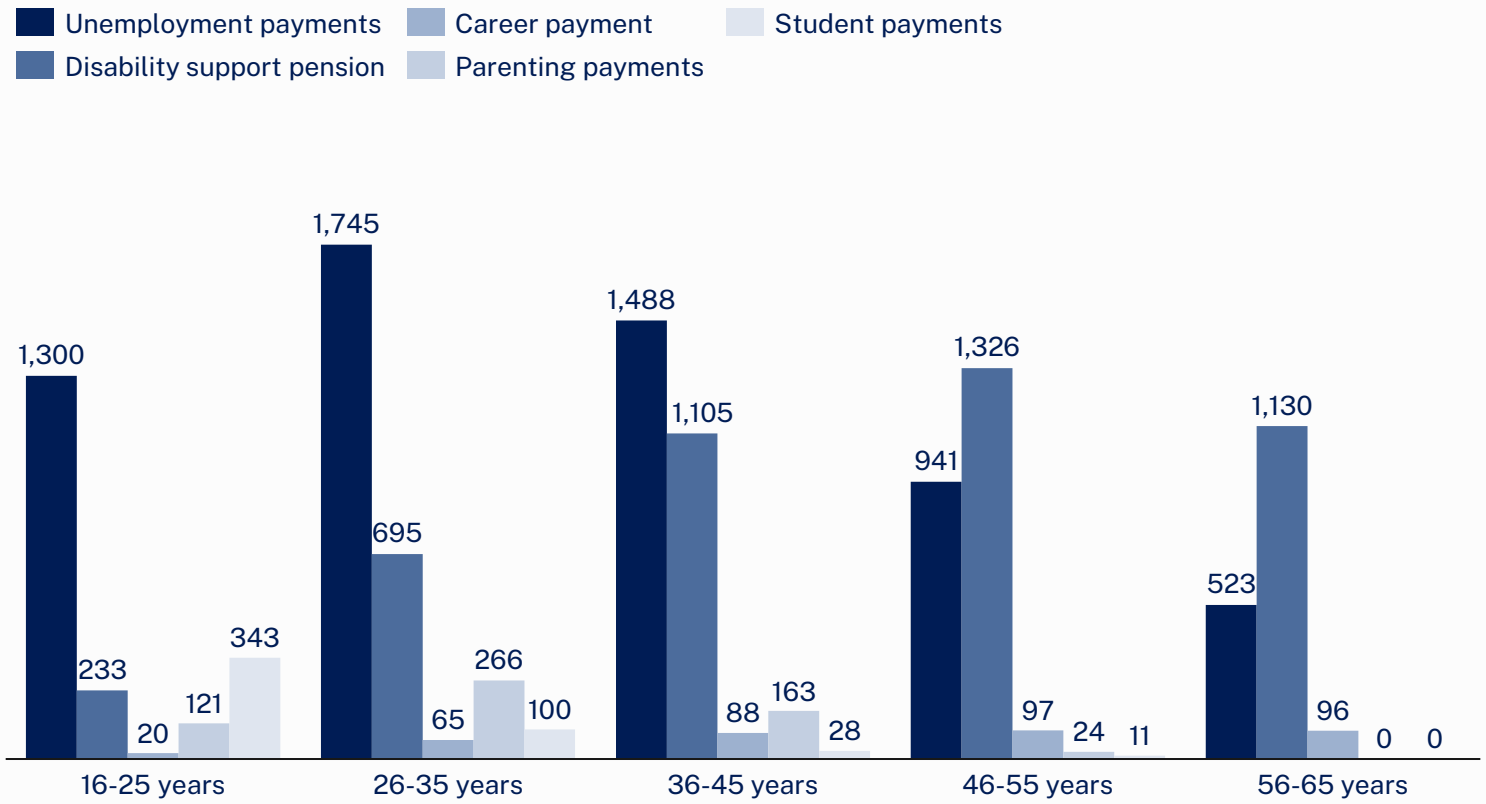
More JobSeeker recipients died by suicide between 2011 to 2021 than any other group on income support payments. The number of deaths by suicide by those receiving JobSeeker were highest among the 16-25 years, 26-35 and 36-45 age brackets compared to those receiving other payment types.

The Productivity Commission estimates the cost of a life lost due to suicide at $9.4 million in 2020.[1]

A 2018 report by Mental Health Australia (MHA) and KPMG states that suicide cost the Australian economy more than $1.6B in 2016 with 2,866 lives lost annually.[2]

Exhibit 22: Number of deaths by suicide among those who received income support payments

Total number of deaths by suicide across the decade from 2011 to 2021



Source: AIHW (2024), *Supporting people who experience socioeconomic disadvantage: Deaths by suicide among Centrelink income support recipients*

1 Productivity Commission (2020) *Mental Health Inquiry*. 2 KPMG (2018), *Investing to save: the economic benefits for Australia of investment in mental health reform.*

Improving mental health outcomes can reduce the cost of lives lost due to suicide

Increasing unemployment benefits can reduce financial and psychological distress and may reduce suicide rates.

Three studies (Antonakakis and Collins, 2015; Cylus et al., 2014; Norström and Grönqvist, 2015) find evidence that higher unemployment benefits are associated with a reduction in suicide rates.[1]

Antonakakis and Collins (2015) studied the effects of austerity measures on suicide rates in five peripheral Eurozone countries. They found that this relationship was influenced by unemployment benefits and employment protection laws. The impact varied based on age, gender, and specific policies. Notably, a one-unit increase in unemployment benefit replacement rates led to a 0.55% reduction in suicide rates among individuals aged 25–44 and a 0.33% reduction for males aged 65–89.[2]

In a study of U.S. states, Cylus et al. (2014) examined how the generosity of unemployment benefit programs affected suicide rates during economic downturns. They defined generosity as the maximum unemployment benefit amount multiplied by the maximum eligibility duration within a year. States with benefits above the average ($7,990 per person per year) experienced smaller increases in suicide rates as unemployment rose, compared to states with lower benefits. Their findings suggest the impact of unemployment rates on suicide is offset by the presence of generous state unemployment benefit programs, though estimated effects are small in magnitude.[3]

Norström and Grönqvist (2014) examined the link between increases in unemployment and suicide using time-series data for 30 countries spanning the period 1960–2012. Separate fixed-effects models were estimated for each of five welfare state regimes with different levels of unemployment protection (Eastern, Southern, Anglo-Saxon, Bismarckian and Scandinavian). Their findings showed more generous unemployment systems protect against suicide in cases of rising unemployment. There was a significant gradient in the effects among males, with the strongest relationships found between unemployment and suicide in the groups with the lowest unemployment benefits (Eastern Europe: elasticity = 0.28; Southern Europe: elasticity = 0.166), and the weakest effects in the two groups with the highest benefits (Bismarckian: elasticity = 0.038; Scandinavian: elasticity=0.030).[4]

Choi et al. (2021) in a Korean study, find persistent financial hardship has a cumulative effect on suicide ideation, which increases with age.[5]

A US study comparing the generosity of state earned income tax credits found a 10-percentage point increase in state earned income tax credit reduced suicide attempts by 4 per 10,000 annually. The study suggested income support policies may be one way to reduce suicide attempts and death, especially among low-income adults.[6]

Sources: 1. Shand et al. (2021). 2. Antonakakis and Collins (2015). 3. Cylus et al. (2014). 4. Norström and Grönqvist (2014). 5. Choi et al. (2021). 6. Morgan et al. (2020). Mandala analysis.

The literature shows physical health outcomes improve when incomes increase

One third of low-income households are spending more than 10% of their income on healthcare.[1] One in four Australian adults with select physical health conditions were avoiding care due to costs.[2]

Low-income households spend 40-59% less than higher-income households in absolute terms but a greater share of their relative incomes on medicines and health practitioner visits[3], despite being more likely to have a health condition.[4] In US studies, fewer primary healthcare visits are associated with more ED visits, more hospitalisations, and higher costs.[5]

Aittomäki et al. (2012) tested causality, finding low household economic resources predicted future health problems, and health problems predicted deterioration in labour-market advantage.[6]

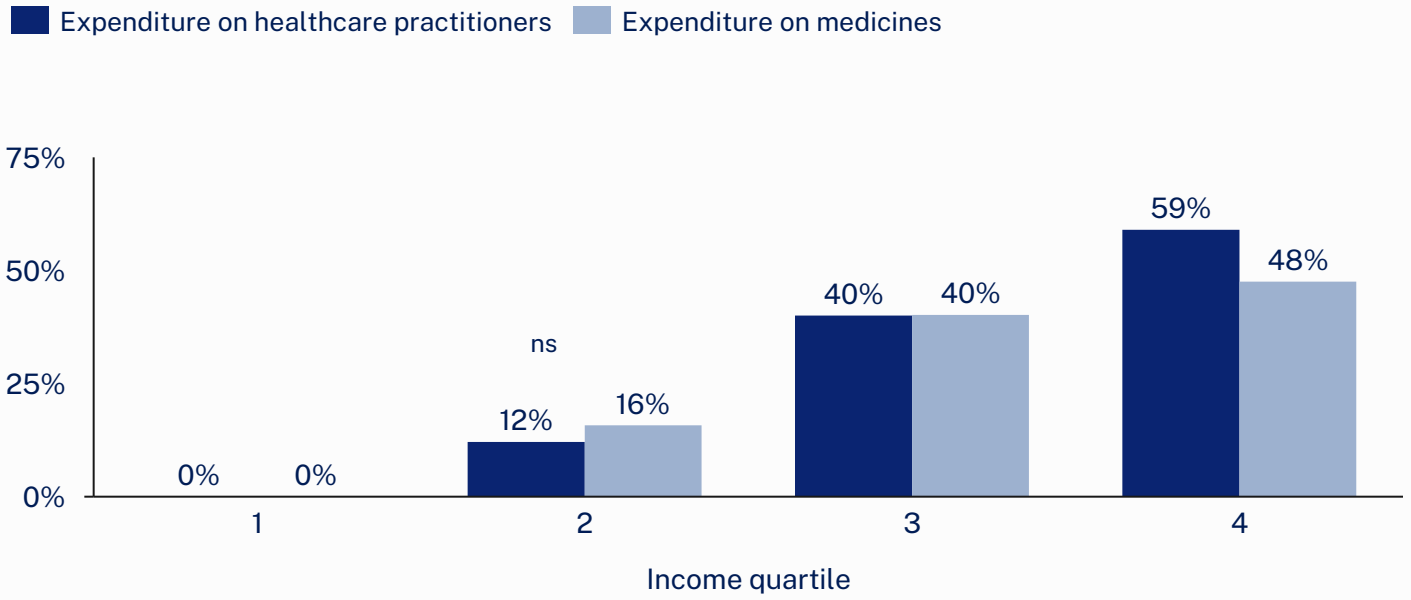
Tøge (2016) found decreases in self-reported health due to becoming unemployed were 19% weaker after controlling for changes in financial strain.[7]

In Canada, unemployment benefits reduce the probability of reporting poor self-rated health among the unemployed by up to 4.9%, with effects highest for low-income individuals.[8] In the US, a 63% increase in benefits was found to completely offset the impact of unemployment on self-reported health.[9]

1. Callander et al. (2019) . 2. Callander et al. (2017) 3. Best & Tuncay (2022). 4 Callander et al. (2019). 5. Rose et al. (2018); Gao et al. (2022). 6. Aittomäki et al. (2012). 7. Tøge (2016). 8. Shahidi et al. (2019). 9. Cylus et al. (2015)

Exhibit 23: The relationship between income and expenditure on healthcare in Australian households

From 2014 and 2018 HILDA data, y-axis = % increase in expenditure compared to quartile 1, x-ais = income quartile



Income quartile 1 (the lowest 25% of earners) is the reference group for the study

Moving from income quartile 1 to income quartile 2, Australian households increase expenditure on medicine by 16%

Overall, Best and Tuncay (2022) found for every $1 increase in income, there's a $0.20 increase in spending on health practitioners

Source: Best & Tuncay (2023) *Understanding household healthcare expenditure can promote health policy reform.* See Table 4 and Table 6, model 2; Mandala analysis.

The literature shows children's development outcomes improve when incomes increase

Early-life conditions — poverty experienced in childhood and in utero — increase the likelihood of poor nutrition and other stressors, resulting in impaired cognitive development and adult mental illness.[1] Parental mental illness can also influence children's cognitive development and educational attainment, transmitting mental illness and poverty across generations.[1]

Nicholson et al. (2012) used the Longitudinal Study of Australian Children to examine how family income, parents' hours of work and the quality of parents' jobs affect childhood development.[8]

Comparing children from the most disadvantaged backgrounds to children from the most advantaged families, the study found:

- 37% more children from the most disadvantaged backgrounds had poor cognitive outcomes,
- 19% more exhibited poorer socio-emotional adjustment, and
- 11% more had problems with their physical health.[8]

1. Ridley et al. (2020). 8. Nicholson et al. (2012).

Exhibit 24: Income is related to child outcomes via two main channels

Country of study

1 Increasing expenditure on children	2 Reducing family stress
For every 1% increase in total household expenditure, spending on preschool and primary education rises by approximately 1.45%.[2]	Financial stress increases the risk of mental distress. In turn, poor parental health can then lead to negative parenting behaviours, lack of attention, and increased dysfunction.[5]
Gregg et al. (2006) find expenditure on children's clothing and footwear, toy and books increases with income, while spending falls for alcohol and cigarettes.[3]	Doidge et al. (2017) found poverty (retrospectively assessed) was associated with a 1.9 times increase in the risk of any child maltreatment (physical / emotional / sexual abuse, neglect and witnessing domestic violence).[6] Further, 27% of all child maltreatment was jointly attributable to economic factors.[6]
Raschke (2012) found variations in German child benefit payments lead to increased food expenditure in low-income families.[4]	Cancian et al. (2013) found significant reductions in the risk of child abuse and neglect from increased child support payments.[7]

Sources: 2 Jääskelä & Windsor, (2011). See Appendix A. Results are for 2009/2010. 3 Gregg et al. (2006). 4 Raschke (2012). 5 Kamis (2021). 6 Doidge et al. (2017). 7 Cancian et al. (2013).

Increasing income or benefits improves childhood development outcomes

International evidence shows increases in income are associated with improvements in children's cognitive, social and health outcomes.

A systematic review of randomised control trials (RCTs), quasi-experimental studies and observation studies using fixed effect longitudinal studies showed income positively impacted child outcomes in 63% of studies.[4]

The results highlight the positive causal effect of household income on children's outcomes, including their cognitive and social-behavioural development and their health, particularly in households with low income to begin with. The results also show clear evidence of a positive causal effect of income on 'intermediate outcomes' that are important for children's development, including maternal mental health, parenting and the home environment.

The review identifies studies with the following effects sizes related to a US$1,000 increase in annual income was associated with a *x*% standard deviation improvement in childhood development outcomes across:

- **Cognitive outcomes:** Gennetian and Miller (2002) look at school performance in the US find an effect size of 10%. Elstad and Bakken (2015) find an effect size of 1% on school grades in Norway, and found more noteworthy effects for the 5% of families with the lowest incomes, suggesting that in these families, lack of income hinders children's school performance.[3]
- **Social outcomes:** In Canada, Milligan and Stabile (2011) found a 10% effect size for reductions in anxiety and physical aggression.[4] In the US, Hamad and Rehkopf (2015) found a 3% effect size on the Behaviour Problem index.[5]
- **Health outcomes:** Mocan et al. (2015) and Chung, Ha and Kim (2016) in US studies found a 1% effect size of income on birthweight.[6]

An Australian study by Khanam and Nghiem (2016), examined family income effects on children's cognitive development. They control for parental investment, parental stress, and neighborhood characteristics to examine if these factors mediate the effects of income. The study finds that family income is significantly associated with children's cognitive skills.[7] Bernal and Keane (2011) find test scores at ages 5-6 are significantly correlated with educational attainment measured at age 18.[8]

Welfare cuts in the US adversely affected engagement in parent-child activities[9] and were significantly associated with approximately 0.3–0.4 standard deviation lower scores on provision of emotional support by parents.[10]

A 2024 study examined the effects of a large welfare benefit reduction for adult refugees who received residency in Denmark, which reduced their disposable income by 30% on average over the first five years. It found that children exposed to the welfare cut during preschool and school-age obtained lower GPAs, had reduced well-being and overall education levels, and suffered lower employment and earnings as adults. Teens at exposure faced large increases in conviction probabilities for violent and property crimes.[11]

Sources: 1. Cooper and Stewart (2020). See Tables 5, 6, 7. 2. Gennetian and Miller (2002). 3. Elstad and Bakken (2015). 4. Milligan and Stabile (2011). 5. Hamad and Rehkopf (2015). 6. Mocan et al. (2015); Chung et al. (2016). 7 Khanam & Nghiem (2016). 8. Bernal & Keane (2011). 9. Reichman et al. (2020). 10. Kalil et al. (2022). 11. Dustmann et al. (2024).

After accounting for publication bias, a typical replacement rate-duration elasticity is 0.36

Cohen and Ganong (2024) undertook a meta-analysis of 54 studies, found that after accounting for publication bias and study characteristics, a typical replacement rate duration elasticity is 0.36.[1]

Vivalt et al. (2023) studied a randomised control trial (RCT) where 1,000 low-income adults in the US received $1,000 per month for three years, with the 2,000 control participants receiving $50 over that same time period. The program resulted in a 2.0 percentage point decrease in labour market participation for participants and a 1.3-1.4 hour per week reduction in labour hours.[2]

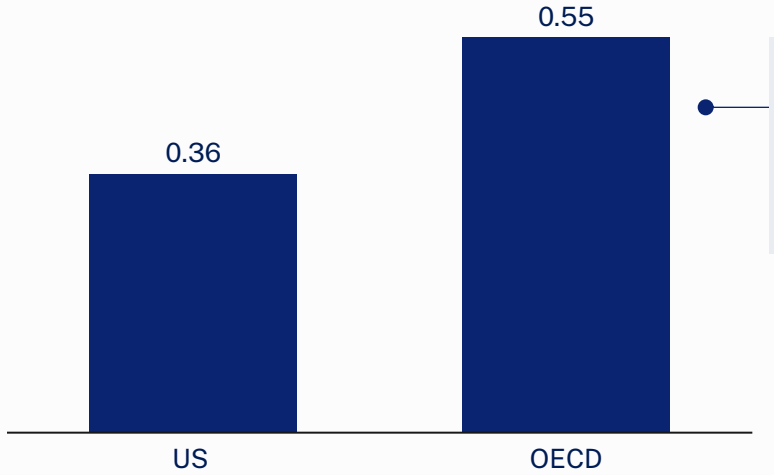
Le Barbanchon et al. (2024) found the median 'behavioural cost' in the US for each additional $1 transfer in unemployment benefits was $0.35-$0.81, depending on assumptions.[3] Replacement rates in the US tend to be higher than Australia not necessarily because their unemployment payment rates are relatively more generous but because their minimum wages are relatively lower.

The EIAC (2024) suggests a substantial increase to JobSeeker would not affect work incentives, as they would still earn less than 97.5% of employed Australians.[4] Buddelmeyer et al. (2009) also find only weak evidence that low-wage employment is a conduit for repeat unemployment.[5]

1 Cohen & Ganong (2024). 2 Vivalt et al. (2024). 3 Le Barbanchon et al. (2024). 4 EIAC (2024). 5. Buddelmeyer et al. (2009).

Exhibit 25: Elasticity of time spent on unemployment payments

Based on a 1% increase in replacement rate, weighted median across studies, by region



Cohen and Ganong (2024) found that:

- In US studies, a 1% increase extends unemployment duration by 0.36% from a baseline replacement rate of 43.5%. In studies across OECD countries, it's higher at 0.55% from a 62% replacement rate baseline.
- The average replacement rate observed in the US studies was **43.5%** and last 26 weeks in most states.
- The average replacement rate across OECD studies was **62%,** and the potential benefit duration was 80 weeks.
- This indicates elasticities increase as the base replacement rate and base potential benefit duration increases. Notably, Australia's replacement rate is **32%**.

Source: Cohen & Ganong (2024); Mandala analysis.

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MANDALA

Appendix B: Microsimulation Approach and Regression Tables

APPENDIX B

Glossary of key technical terms

TERM	DESCRIPTION
Regression	Regression models are a statistical technique to analyse the relationships between different factors and an outcome variable. We use regressions to estimate the effect of each factor on the outcome we are modelling, while controlling for potential confounding variables.
Odds ratio	Odds ratios help us with interpretating the results of logistic regressions, by transforming the coefficients produced by the regression. They help us explain how each factor is associated with the outcome we are modelling **relative to a comparison factor**. For example, if we found the association between not having a child (relative to having a child – the comparison factor) and being under financial stress has an odds ratio of 0.543, we could say that an individual who does not have a child is 0.543 times as likely to be under financial stress as an individual with a child, **holding all other factors constant**.
Confidence interval	Confidence intervals provide statistical bounds for the effect sizes (coefficients and odds ratios) calculated by each regression. They help us conceptualise the range of the values possible in different samples. All confidence intervals reported in the regressions tables are 95% confidence intervals. As an example, if a variable has a 95% confidence interval for the odds ratio of (1.5, 2.0), this means that we expect the average odds ratio to fall between 1.5 and 2.0 95% of the time.
P-value	Each regression includes p-values for our estimates on how different factors of the study cohort are associated with an outcome. The p-value is a probability that helps us evaluate whether the observed differences between individuals in the cohort is due to random chance, or if it is associated with the factor (e.g. higher income). A small p-value indicates that it is less likely that the observed differences between individuals in the cohort are due to random chance and are instead due to the factors studied. See statistical significance below for further information.
Statistical significance	Statistical significance and p-values are closely related. Statistical significance helps measure whether observed differences in the data of outcomes are likely due to random chance or not. For example, if the p-value associated with logged income and financial stress is below 1% (i.e. $p < 0.01$), we can deduce that “the effect of logged income on financial stress is statistically significant at the 1% level”. In our regression analysis, we call out statistical significance at the 10% (*), 5% (**) and 1% (***) levels.

Source: Mandala analysis.

Approach to modelling an increase to the JobSeeker Payment

This report examines the impacts of increasing the JobSeeker Payment to 90% of the Age Pension rate. The analysis considers both the direct costs to government and the broader social and economic benefits stemming from this investment, with particular focus on health outcomes, labour market participation, and childhood development impacts.

This analysis considers the dual objectives of providing an adequate income support level to prevent poverty and enabling returns to work. The adequacy of current payment levels in supporting participants to springboard back into employment has been questioned. JobSeeker Payment rates have fallen to 32% of previous wages, the second lowest replacement rate in the OECD at the two-month mark.[1]

Regarding the adequacy of current payment levels, 47% of recipients are on payment for over 2 years, suggesting barriers to employment transitions.[2] 43% have partial work capacity, indicating complex barriers to full-time work.[2] High rates of psychological distress (45% vs 24% for non-recipients) may impede job search.[3] Psychological distressed is worsened by high rates of experiencing more than three measures of financial strain (26% vs 5% for non-recipients), which reduces resources for job search.[4]

This report presents the results of a bespoke microsimulation model designed to understand the impacts of a rise in JobSeeker Payment level. The analysis relies heavily on primary econometric analysis informed (to the extent possible) by the causal pathways identified in the literature to examine the relationship between income and socio-economic factors. Bespoke modelling helps project results for a low-income Australian cohort.

The microsimulation is applied to a representative cohort to simulate 20,000 individuals over a 10-year period. Demographic matching aligns the characteristics of the cohort with the current JobSeeker cohort.

The simulation models individual transitions through labour force outcomes. It forecasts financial stress, health, and childhood development outcomes.

The benefits of improved incomes that were readily quantified are:

1. **Physical and mental health outcomes:** lower financial stress and improved mental health (Kessler-10 scale), fewer declines in physical health, reduced GP visits and hospitalisations; and additional Quality-Adjusted Life Years (QALYs).
2. **Economic outcomes:** lower financial stress, stronger labour market transitions via improved mental health, lower rates of crime, boosts to individual income and economy-wide productivity.
3. **Childhood development outcomes**: lower childhood poverty, higher childhood educational attainment and lower lifetime social security system use for children of the cohort.

The analysis focuses on incremental improvements attributable to the JobSeeker increase compared to current payment levels.

All monetary values are expressed in 2024 Australian dollars. Future costs and benefits are discounted using a real rate of 7% per annum in line with Australian Government guidelines, with sensitivity testing at 3% and 10%.

Sources: 1. OECD (2022). 2. Mandala analysis of DOMINO data (2024). 3. Mandala analysis of HILDA data (2024).

Understanding our microsimulation approach

The microsimulation creates a 'virtual population' that mirrors the characteristics and behaviours of real people, allowing analysis of how policy changes affect different groups in society. We used this approach to model 20,000 simulated individuals over 10 years, tracking changes in their health, employment, financial circumstances and their children's outcomes when JobSeeker Payment increases to 90% of the Age Pension rate.

COMPONENT	DESCRIPTION
Microsimulation modelling	▪ Microsimulation is a modelling technique that simulates life outcomes for individuals and their families over time. The approach creates a 'virtual population' that mirrors the characteristics and behaviors of real people, allowing analysis of how policy changes affect different groups in society. ▪ This study employs microsimulation to analyse the effects of raising JobSeeker Payment to 90% of the Age Pension rate (a 32.4% uplift). The model follows 20,000 simulated individuals over 10 years, tracking changes in their health, employment, income and children's outcomes.

Microsimulation framework	▪ The model simulates two scenarios:
	  ▪ A baseline scenario with current JobSeeker Payment rates
	  ▪ An uplift scenario where payments increase to 90% of the Age Pension (a 32.4% uplift)
	▪ For each scenario, the model tracks individuals' transitions through states including labour force status and income, physical and mental health outcomes, financial and psychological distress, healthcare utilisation, and child educational outcomes. We run each scenario 30 times and take the average over these 30 simulations when reporting our final results.

Representative cohort construction	▪ The microsimulation's 20,000-person cohort reflects the characteristics of JobSeeker recipients who began receiving payments between January and March 2022. The cohort is constructed using analysis of the key demographics of these JobSeekers including spell duration, age and gender, educational attainment, partner status, work capacity, and dependent status (number and age of kids). ▪ This demographic matching ensures the simulated population accurately represents the diversity and complexity of the JobSeeker recipient population.
Actuarial approach	▪ The microsimulation embeds actuarial principles to assess long-term costs and benefits. For each simulated individual, the model tracks future payment and income streams, transitions between payment levels, and mortality risks using Australian Life Tables. This allows us to project lifetime costs under both current and increased payment scenarios, incorporating risk adjustments and standard government discount rates. ▪ The actuarial valuation converts simulated outcomes into monetary values. It quantifies direct costs like increased payments, but also captures future benefits such as improved health outcomes (measured through Quality Adjusted Life Years), productivity gains from better mental health, and intergenerational effects through childhood development.

Source: Mandala analysis.

The microsimulation model draws on various data and statistical approaches

The analysis underpinning this report draws on a range of different data sources, including:

Administrative Data

- Unit-record Data Over Multiple Individual Occurrences (DOMINO) data from the Department of Social Services (DSS) data on JobSeeker recipients
- Unit-record Participant Level Integrated Data Asset (PLIDA) Medicare Benefits Schedule (MBS) claims data

Longitudinal Survey Data

- Household, Income and Labour Dynamics in Australia (HILDA) Survey Waves 1-22
- Longitudinal Study of Australian Children (LSAC)
- Longitudinal Surveys of Australian Youth (LSAY)

Secondary Data

- Australian Life Tables 2015-17 (ALT) from the Australian Government Actuary, providing mortality rates.
- Australian Bureau of Statistics (ABS) population and labour force data
- Australian Institute of Health and Welfare (AIHW) data
- Priority Investment Approach actuarial valuation data
- Services Australia payment rates and eligibility criteria

Various statistical regression techniques are used to appropriately model the relationship between income and key outcome variables depending on their distribution and characteristics.

Survival analysis techniques incorporating ALT 2015-17 mortality rates (qx) were employed to account for demographic attrition in longitudinal projections. This allows for more accurate modelling of long-term outcomes by incorporating age and gender-specific mortality risks. The analysis uses period life tables with mortality rates (qx) differentiated by age and sex.

Binary logistic regressions are used for dichotomous outcomes such as JobSeeker status, employing a logit link function to model outcome probabilities. For outcomes with multiple categories, such as GP visit frequency bands, multinomial logistic regression is applied for maximum likelihood estimation to calculate relative risk ratios.

Ordinal regressions are applied for ordered categorical variables like duration on JobSeeker, accounting for the sequential nature of these outcomes and estimating cumulative probabilities across categories.

Linear regression using ordinary least squares estimation is used for continuous outcomes including psychological distress and NAPLAN scores, directly modelling linear relationships between variables.

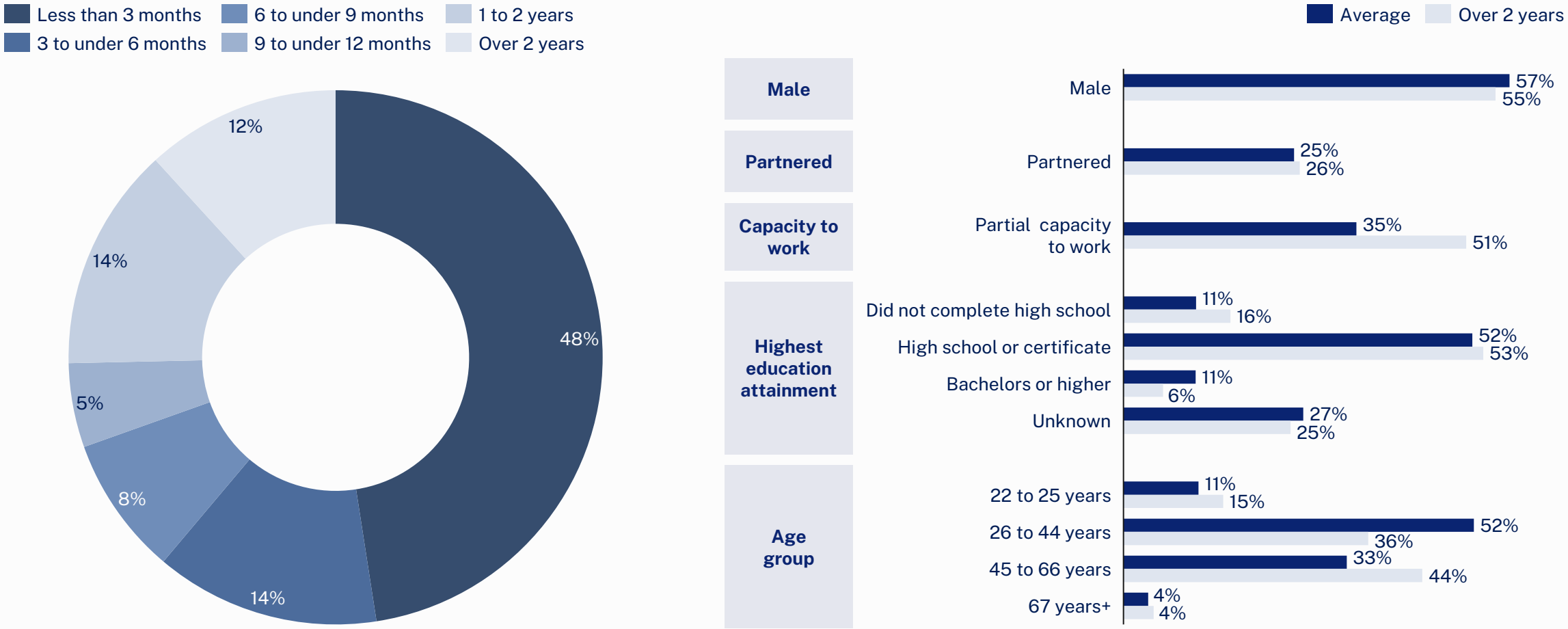
Models control for a range of factors depending on the regression (refer to each coefficient table to understand the variables included). These control variables help to isolate the effects of key outcome variables by accounting for confounding factors, and variously include:

- Demographics: age, gender, living with/without partner, presence and age of dependents);
- Labour force status; educational attainment;
- Health status: health scores, psychological distress measures, prior health conditions/capacity to work; and
- Time-related controls: COVID period indicator, previous JobSeeker status, the duration of benefit receipt.

The models report various goodness-of-fit measures including Area Under the ROC Curve (AUC) for logistic models and R-squared for linear regressions. Refer to the Appendix for further detail.

We model a representative cohort that flows onto the JobSeeker Payment in a three-month window; based on Q1 2022 data observed until June 2024

Exhibit 26: Jobseeker cohort breakdown by continuous[1] payment receipt (spell length)



1 Durations on payment were calculated in DOMINO as being continuous if the lag between a period of payment or suspension was less than 52 days. Source: DOMINO 2024; Mandala analysis.

82,609 (58%) JobSeekers who started receiving the JobSeeker Payment in Q1 2022 have children; 18% of those with children have a child younger than 18

Exhibit 27: JobSeeker Payment recipients by number of children

% of JobSeeker cohort segmented by number of children

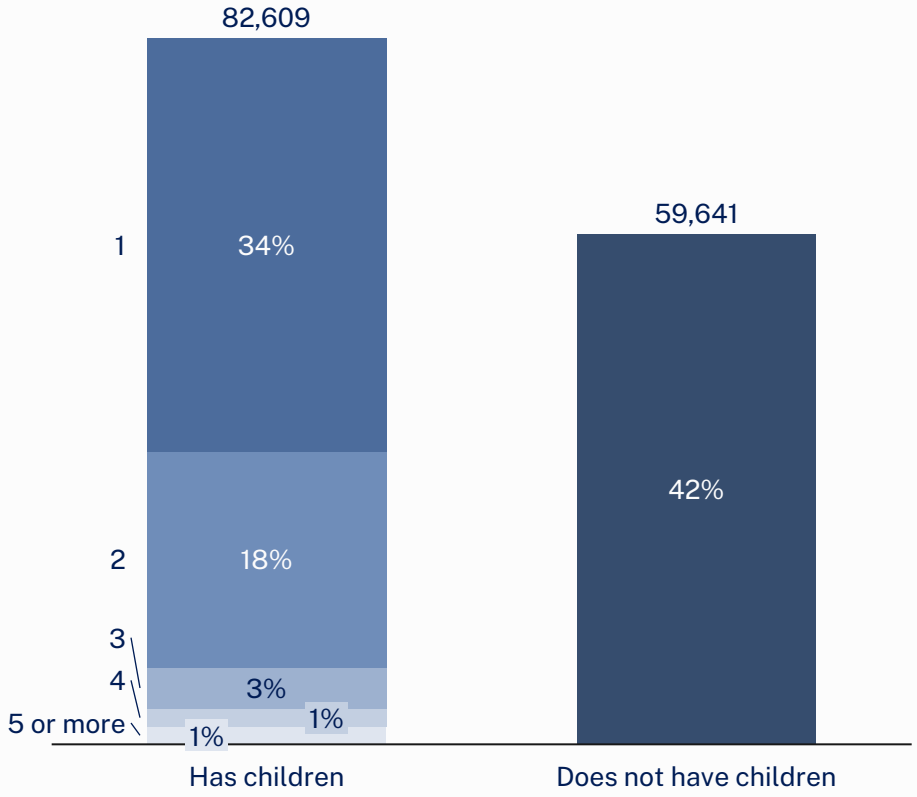
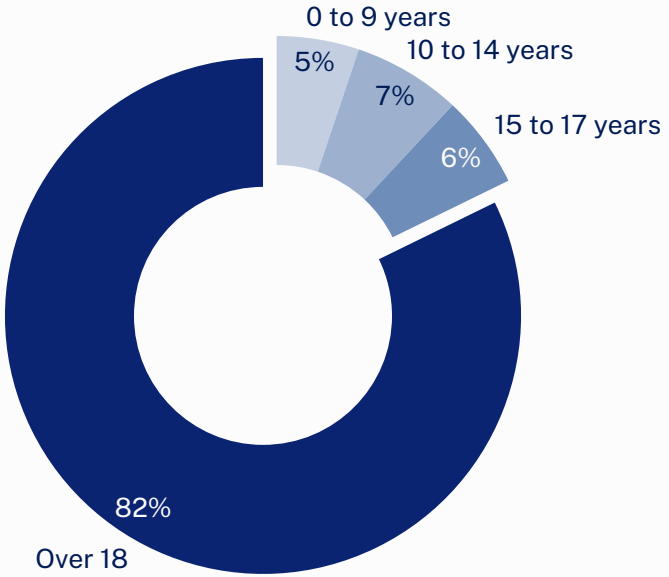


Exhibit 29: 18% of JobSeekers with children have a youngest child under 18

% of those with children segmented by age of youngest child

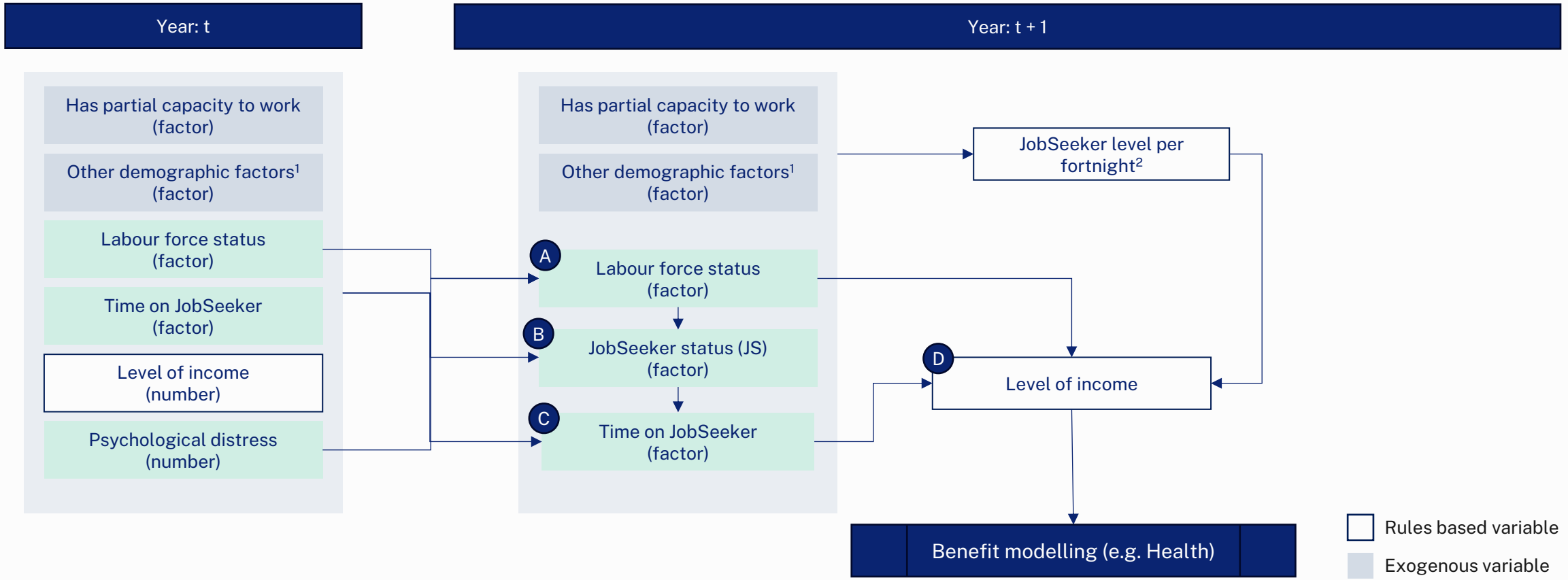


Age of youngest child	0-9 years	10-14 years	15-17 years	Over 18
Number of JobSeekers	4,260	5,600	4,810	67,930

Source: DOMINO, Mandala analysis.

We model an increase to JobSeeker using a microsimulation to simulate lifepaths of the representative cohort

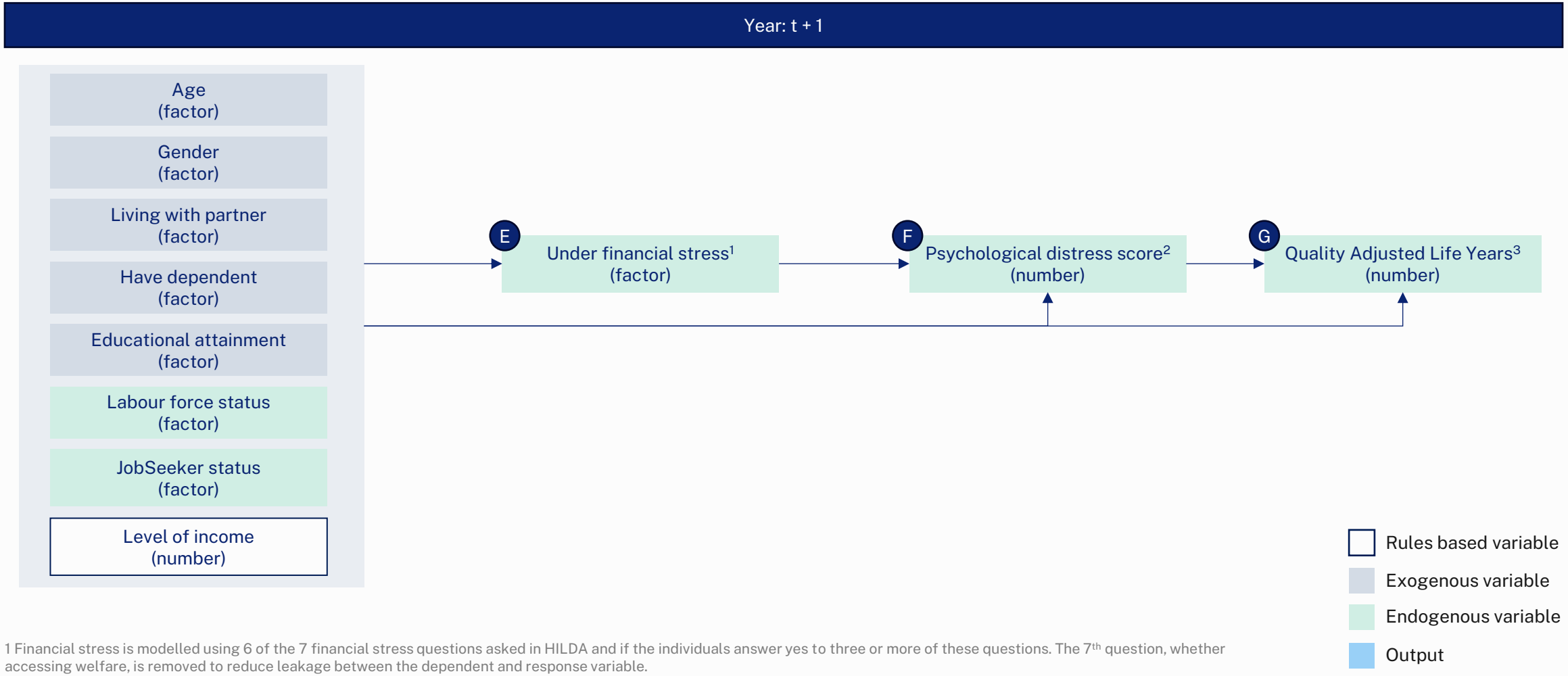
LABOUR FORCE AND JOBSEEKER MODELLING IN THE MICROSIMULATION



1 Other demographic factors include age band, gender, whether living with partner, whether they have dependent children, and highest level of educational attainment.
2 JobSeeker level per week is dependent on exogenous variables (for example living with a partner and having a dependent child), and is calculated using Services Australia's rules.

Social welfare and mental distress are measured in the microsimulation through the modelling of financial stress of the cohort and their psychological distress

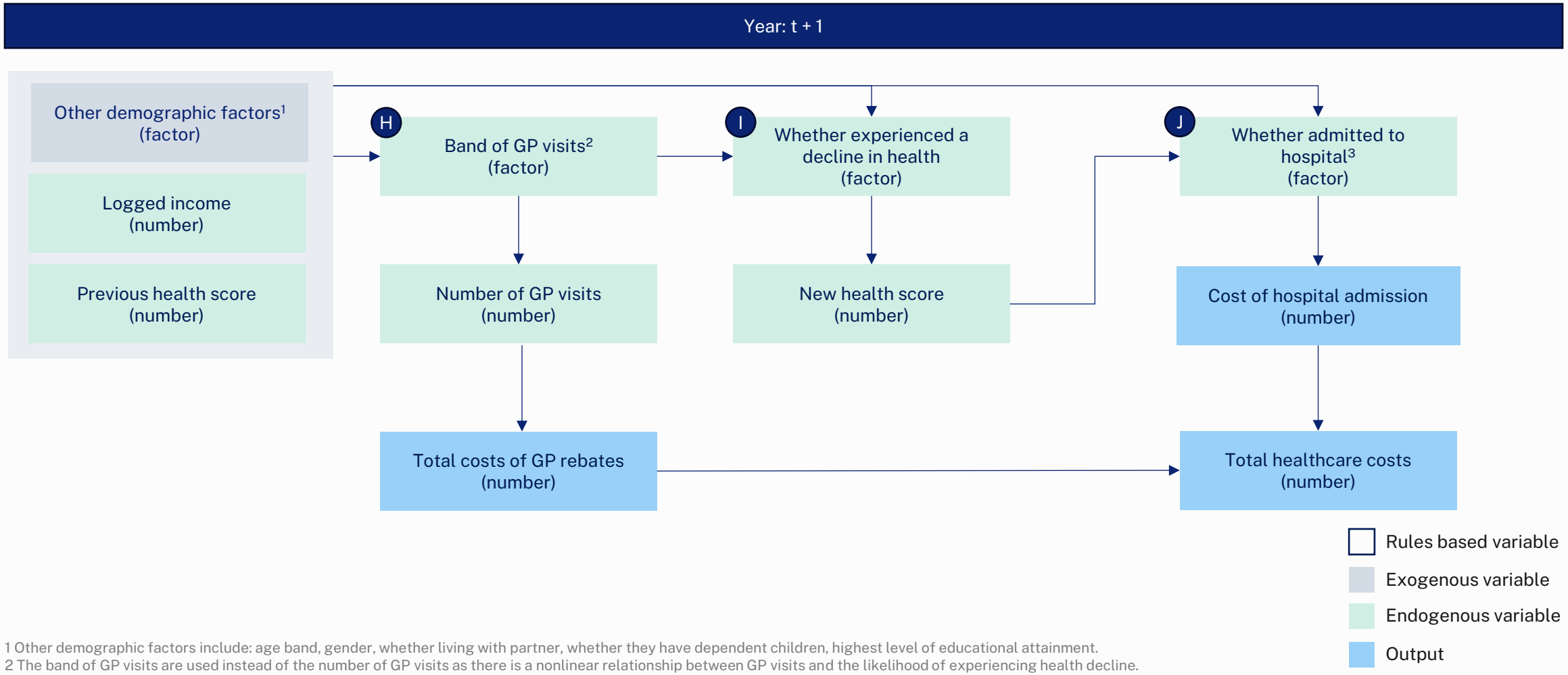
FINANCIAL STRESS AND PSYCHOLOGICAL DISTRESS MODELLING



1 Financial stress is modelled using 6 of the 7 financial stress questions asked in HILDA and if the individuals answer yes to three or more of these questions. The 7th question, whether accessing welfare, is removed to reduce leakage between the dependent and response variable.
2 Psychological distress is modelled based on the grouped K10 scores of psychological distress (risk categories): 1 – Low, 2 – Moderate, 3 – High, 4 – Very high.
3 Quality Adjusted Life Years is modelled using the SF-6D health state classification HILDA variable (ghsf6d).

Health costs are calculated by modelling the number of GP visits and hospital admissions in the microsimulation

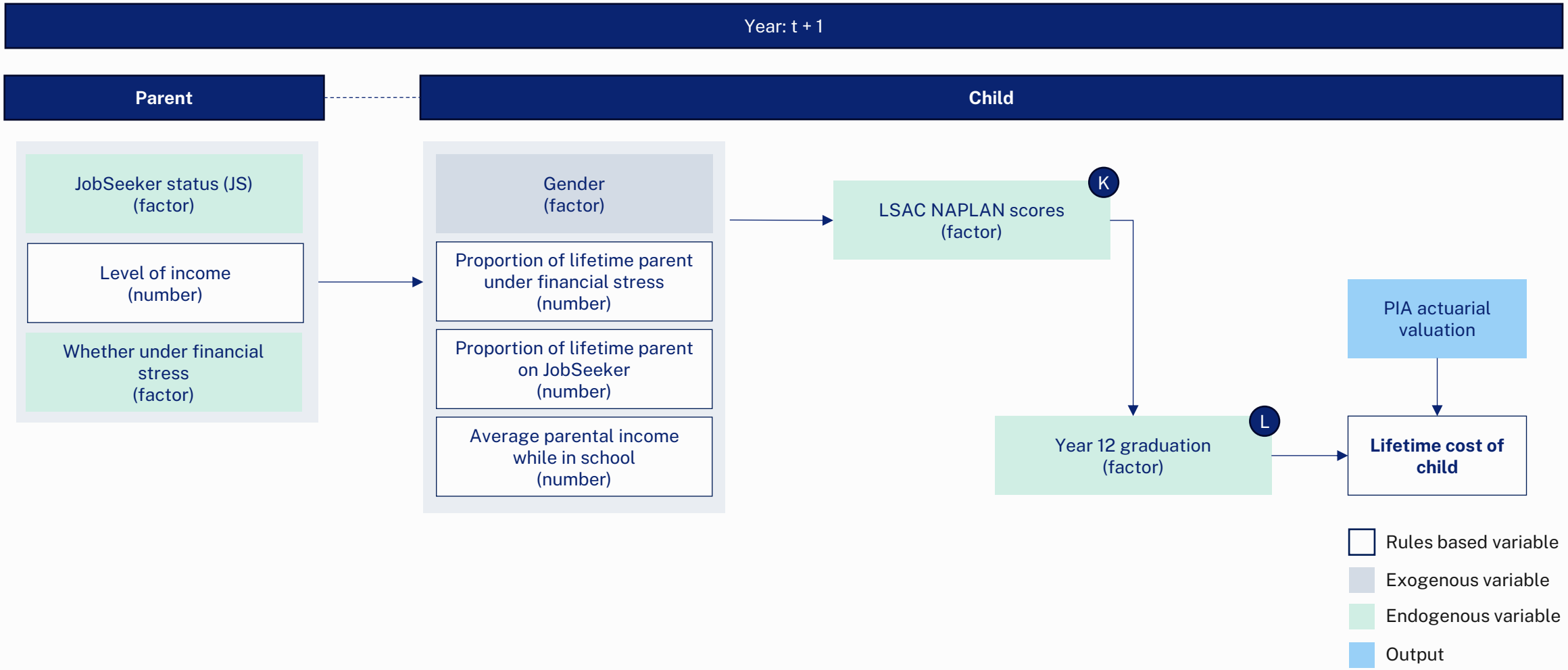
HEALTH COST MODELLING IN THE MICROSIMULATION



1 Other demographic factors include: age band, gender, whether living with partner, whether they have dependent children, highest level of educational attainment.
2 The band of GP visits are used instead of the number of GP visits as there is a nonlinear relationship between GP visits and the likelihood of experiencing health decline.
3 Whether admitted to hospital or not during the year is used rather than a total number as the distribution of number of hospital admissions is right skewed (not many hospital admission). The binary outcome of whether being admitted or not also produces a better fit.

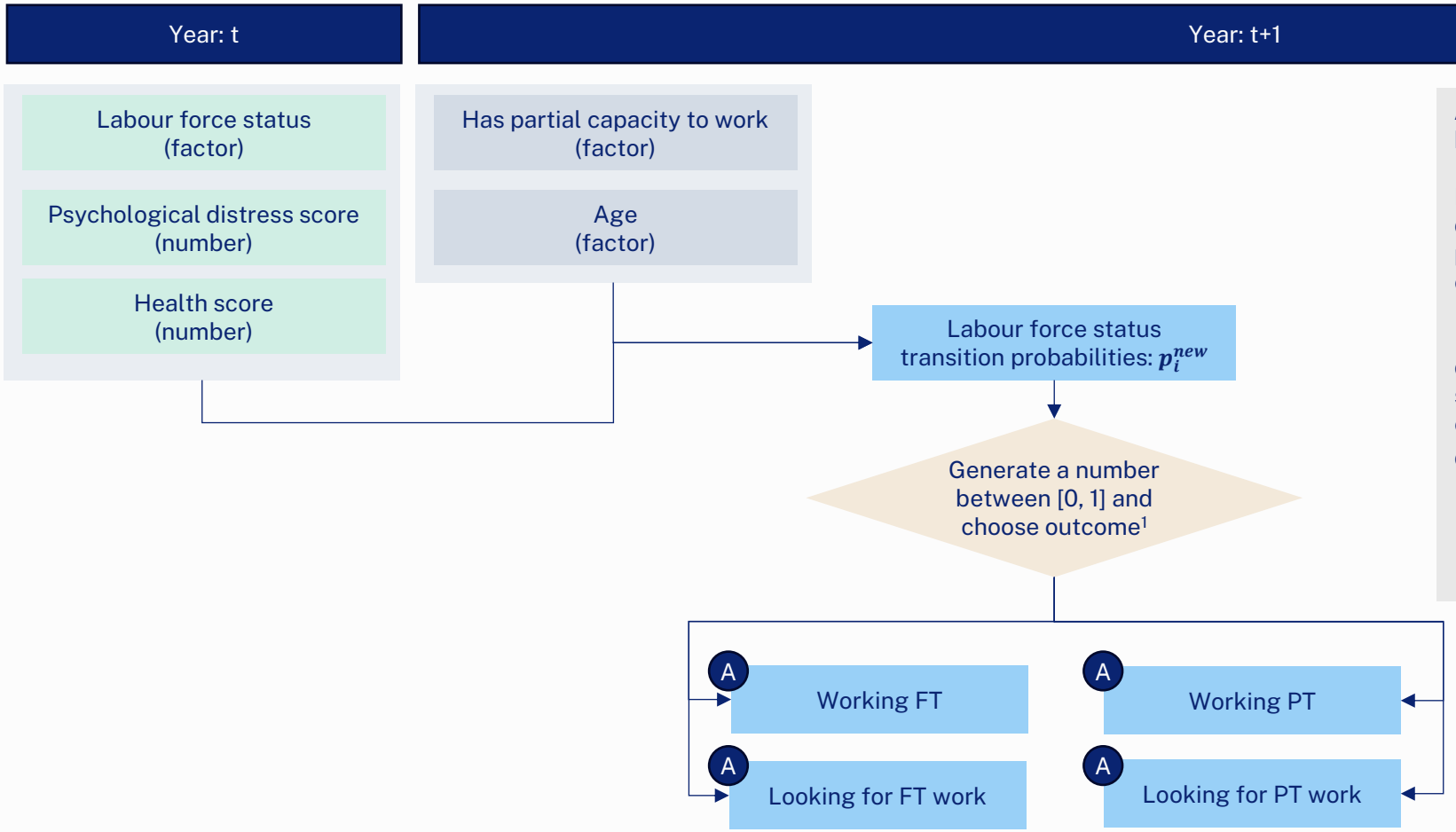
The cost of childhood development is modelled through the association of income with year 9 NAPLAN results and high school educational outcomes

CHILDHOOD DEVELOPMENT COSTS



Labour force status is modelled year to year using probabilities from a transition to employment combined with psychological distress

LABOUR FORCE STATUS MODELLING



A note on modelling: HILDA was used to build the base transition probabilities, by age groups.

However, the literature and additional modelling demonstrates a negative association between psychological distress and the likelihood of gaining employment.

To account for this, we use the psychological distress coefficient from the modelling (β_{PSYCH}) to scale the likelihood of an individual gaining employment by their modelled psychological distress score ($\mu_i^{\widehat{PSYCH}}$).

$$p_i^{new} = \left(1 + \beta_{PSYCH}\left(\mu_i^{\widehat{PSYCH}} - 1\right)\right) p_i^{old}$$

Rules based variable
Exogenous variable
Endogenous variable
Output

1 The combination of the transition matrix and the randomly generated number determines the outcome, as the probabilities in the transition matrix act as ranges for each outcome.

Transitions to employment are shocked by the level of psychological distress to link mental health outcomes and labour force outcomes

LABOUR FORCE STATUS MODELLING

LIKELIHOOD OF GAINING EMPLOYMENT AND HEALTH FACTORS

PSYCHOLOGICAL DISTRESS SCORE[1] (β_{PSYCH})	P-VALUE
-0.173	1.14×10^{-7} ***
HEALTH SCORE[2] (β_{HEALTH})	**P-VALUE**
0.014	7.86×10^{-16} ***

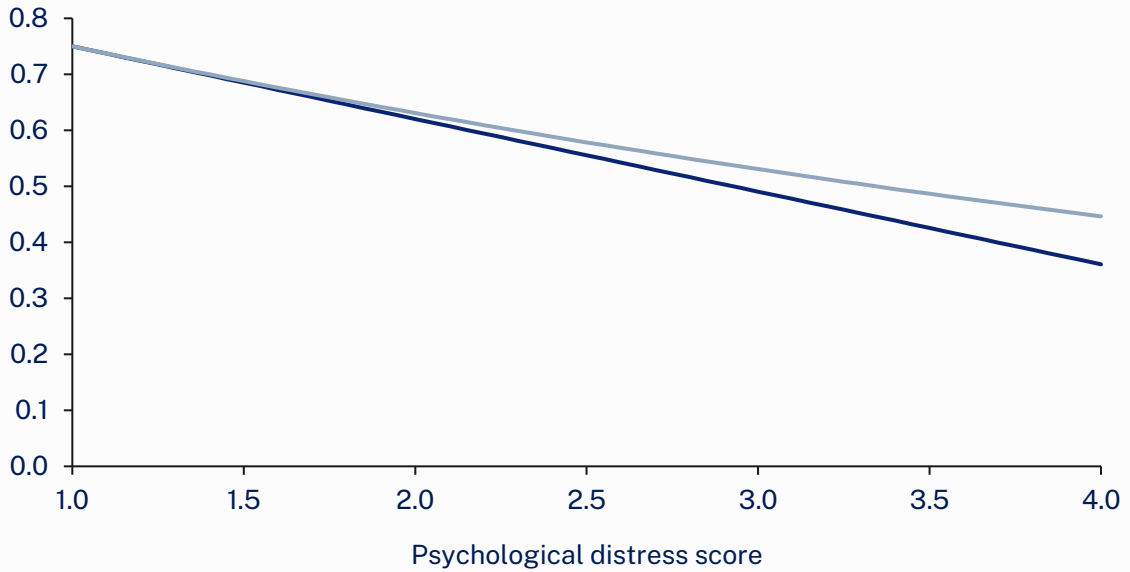
A note on modelling: Improvements in mental health (through a reduction in psychological distress) and improvements in health (through an increase in health score) have strong statistically significant association with an improved likelihood of gaining employment in the next year.

However, when both are included in a regression, these associations diminish, highly likely due to the correlation between the two variables. To account for this, only the psychological distress score was included in the modelling as the literature demonstrates a clearer association between income and mental health via financial stress, including in Australian studies, compared to physical health.[3]

IMPLEMENTATION IN THE MODEL

$$p_i^{new} = e^{\beta_{PSYCH}\left(\mu_i^{\widehat{PSYCH}} - 1\right)} p_i^{old}$$

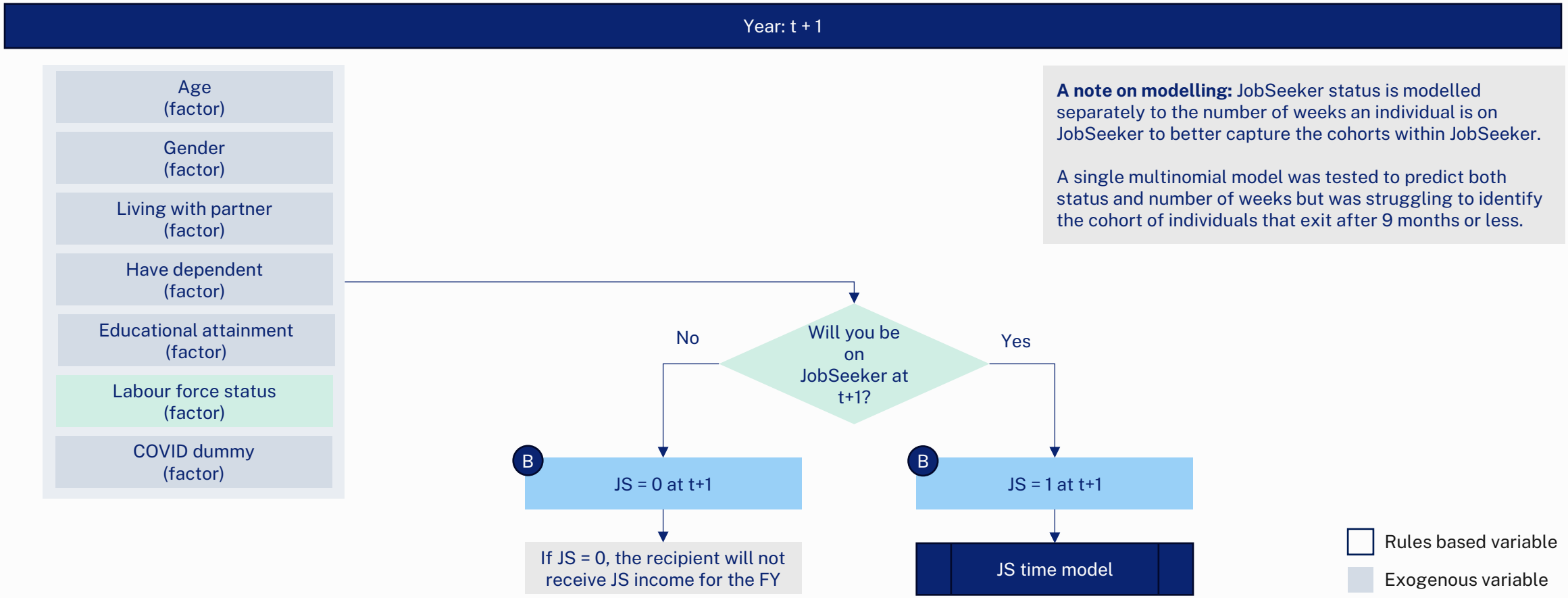
$$p_i^{new} = \left(1 + \beta_{PSYCH}\left(\mu_i^{\widehat{PSYCH}} - 1\right)\right) p_i^{old}$$



1 The psychological distress scores are based on Kessler 10 risk categories and range from 1 to 4, where a higher score indicates higher psychological distress. (HILDA variable pdk10rc).
2 The health score is measured through a transformed score from the SF-36 health survey which is scaled to range from 0-100, where a higher score for an individual is indicative of better health. (HILDA variable ghgh).
3 See for example, Botha, Butterworth and Wilkins (2022) *Protecting mental health during periods of financial stress: Evidence from the Australian Coronavirus Supplement income support payment*, Table 3 & 5.

The JobSeeker status of individuals is modelled after we know their labour force status

JOBSEEKER STATUS MODELLING

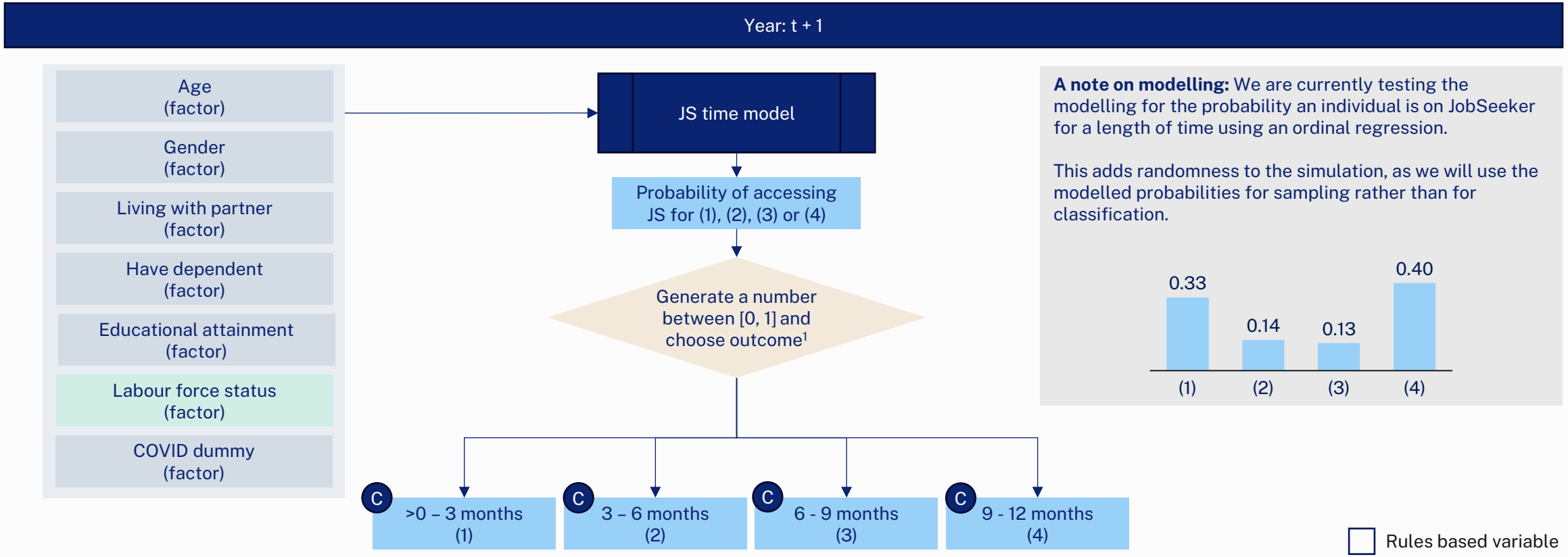


A note on modelling: JobSeeker status is modelled separately to the number of weeks an individual is on JobSeeker to better capture the cohorts within JobSeeker.

A single multinomial model was tested to predict both status and number of weeks but was struggling to identify the cohort of individuals that exit after 9 months or less.

We then model the likelihood that an individual access JobSeeker for different lengths of time during the year, in three-month bands

TIME ON JOBSEEKER MODELLING



A note on modelling: We are currently testing the modelling for the probability an individual is on JobSeeker for a length of time using an ordinal regression.

This adds randomness to the simulation, as we will use the modelled probabilities for sampling rather than for classification.

[1]Generate a number between [0,1], for illustrative purposes:

- If it's between 0.00 and < 0.33 then the outcome is (1)
- If it's between 0.33 and < 0.47 then the outcome is (2)
- If it's between 0.47 and < 0.60 then outcome is (3)
- If it's between 0.60 and 1.00 then outcome is (4)

Rules based variable
Exogenous variable
Endogenous variable
Output

JobSeeker status is modelled using a binary generalised linear model, with the outcome representing whether an individual was on JobSeeker (1) or not (0)

All HILDA waves | *Includes all individuals in HILDA between 22 and 66 years old* | *n = 222,302* | *Logistic regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	-4.018	0.046	0.018 (0.016, 0.020)	$< 2.0 \times 10^{-16}$ ***
Age (relative to 45 to 66 year old age group)	26 to 44 year olds	0.337	0.027	1.401 (1.328, 1.478)	$< 2.0 \times 10^{-16}$ ***
	22 to 25 year olds	0.378	0.036	1.459 (1.36, 1.566)	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	0.482	0.023	1.620 (1.547, 1.696)	$< 2.0 \times 10^{-16}$ ***
Living with partner (relative to living with partner)	Not living with partner	0.974	0.024	2.649 (2.528, 2.776)	$< 2.0 \times 10^{-16}$ ***
Children (relative to has dependent child aged less than 15 years[2])	Has dependent child over 15 years old	0.398	0.056	1.489 (1.335, 1.661)	1.18×10^{-12} ***
	Has independent child	0.351	0.054	1.420 (1.277, 1.58)	8.03×10^{-11} ***
	No children	0.382	0.03	1.465 (1.382, 1.552)	$< 2.0 \times 10^{-16}$ ***
Highest educational attainment (relative to completed high school)	Did not complete high school	0.454	0.035	1.574 (1.47, 1.685)	$< 2.0 \times 10^{-16}$ ***
	Certificate or diploma	0.287	0.034	1.333 (1.247, 1.425)	$< 2.0 \times 10^{-16}$ ***
	Bachelors or higher	-0.557	0.041	0.573 (0.528, 0.621)	$< 2.0 \times 10^{-16}$ ***
Labour force status (relative to employed - part time)	Employed - full time	-1.496	0.033	0.224 (0.21, 0.239)	$< 2.0 \times 10^{-16}$ ***
	Unemployed – looking for full time work	2.41	0.036	11.136 (10.37, 11.959)	$< 2.0 \times 10^{-16}$ ***
	Unemployed – looking for part time work	1.534	0.060	4.636 (4.123, 5.213)	$< 2.0 \times 10^{-16}$ ***
	Not in LF – marginally associated	0.759	0.036	2.136 (1.992, 2.29)	$< 2.0 \times 10^{-16}$ ***
	Not in LF – not associated	-0.134	0.033	0.875 (0.82, 0.934)	4.89×10^{-5} ***
***COVID dummy (relative to non-COVID year)	COVID year	0.357	0.033	1.43 (1.34, 1.526)	$< 2.0 \times 10^{-16}$ ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. 2 From 20 September 2023, extended the Parenting Payment Single to recipients with youngest child aged under 14 years, previously under 8 years. This change included the transfer of around 65,000 single JobSeeker Payment recipients who were a principal carer of a child aged under 14 years to Parenting Payment Single on 20 September 2023. A large proportion of these recipients (over 85%) were long term income support recipients.
To measure performance of logistic regressions (and multinomial logistic regressions), the Area under the ROC curve (AUC) is given. The AUC tells us how well our model can distinguish between the classes we are predicting in the response variable (for example accessing JobSeeker or not). The JobSeeker model has an AUC of 0.82.

An ordinal regression and a multinomial regression were used to model the period on JobSeeker, cut by 3-month intervals

All HILDA waves | *Includes individuals who were on JobSeeker for one week or more in that year* | *n = 10,628* | *Ordinal regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept (relative to less than 3 months)	Intercept 1	-0.967	0.085	0.38 (0.322, 0.449)	0
	Intercept 2	-0.136	0.084	0.872 (0.740, 1.029)	0.105
	Intercept 3	0.595	0.085	1.813 (1.536, 2.140)	2.60×10^{-12}
Age (relative to late working age)	Working age	0.360	0.048	1.433 (1.306, 1.573)	6.37×10^{-14} ***
	Transition to work	0.608	0.061	1.836 (1.63, 2.068)	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	0.119	0.042	1.126 (1.037, 1.223)	0.005 ***
Not living with partner (relative to living with)	Not living with partner	-0.327	0.043	0.721 (0.662, 0.785)	2.86×10^{-14} ***
Children (relative to has dependent child aged less than 15 years)	Has dependent child over 15 years old	0.217	0.106	1.242 (1.010, 1.527)	0.041 **
	Has independent child	0.288	0.104	1.334 (1.088, 1.637)	0.006 ***
	No children	0.344	0.052	1.411 (1.274, 1.563)	3.71×10^{-11} ***
Highest educational attainment (relative to completed high school)	Did not complete high school	-0.885	0.066	0.413 (0.363, 0.469)	$< 2.0 \times 10^{-16}$ ***
	Certificate or diploma	1.008	0.062	2.741 (2.426, 3.098)	$< 2.0 \times 10^{-16}$ ***
	Bachelors or higher	-0.644	0.058	0.525 (0.468, 0.589)	$< 2.0 \times 10^{-16}$ ***
Labour force status (relative to Employed full time)	Employed - full time	-0.815	0.068	0.443 (0.388, 0.505)	$< 2.0 \times 10^{-16}$ ***
	Unemployed – looking for full time work	-0.863	0.110	0.422 (0.34, 0.523)	4.22×10^{-15} ***
	Unemployed – looking for part time work	0.007	0.060	1.007 (0.895, 1.134)	0.907
	Not in LF – marginally associated	-0.219	0.061	0.804 (0.713, 0.906)	3.30×10^{-4} ***
	Not in LF – not associated	0.533	0.074	1.703 (1.473, 1.970)	5.90×10^{-13} ***
Previous JS status (relative to did not access)	Previously accessed JobSeeker last year	-1.311	0.042	0.27 (0.248, 0.293)	$< 2.0 \times 10^{-16}$ ***
COVID dummy (relative to non-COVID year)	COVID year	-0.073	0.061	0.93 (0.825, 1.049)	0.231

The multiclass AUC of this model was 0.66. This model is great at delineating between the low and high users of JobSeeker (less than 3 months and 9-12 months) but struggles to identify individuals on medium-length spells (over 3 months and under 9 months).

GP visits multinomial model: one GP visit per year relative to none

HILDA Wave 17[1] | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,883* | *Multinomial regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[2]
Intercept	-	-4.261	1.265	0.014 (0.001, 0.169)	0.001 ***
Gender (relative to female)	Male	0.28	0.199	1.323 (0.895, 1.956)	0.160
Whether living with partner (relative to living with partner)	Not living with partner	-0.261	0.222	0.770 (0.498, 1.190)	0.239
Age bands (relative to 18 to 21 years old)	22 to 25 years old	0.58	0.459	1.785 (0.726, 4.392)	0.207
	26 to 35 years old	0.406	0.415	1.502 (0.666, 3.386)	0.327
	36 to 44 years old	0.446	0.471	1.562 (0.621, 3.928)	0.34373
	45 to 55 years old	0.323	0.404	1.381 (0.625, 3.049)	0.425
	56 to 66 years old	0.919	0.41	2.508 (1.122, 5.604)	0.025
Current JobSeeker status (relative to not on JobSeeker)	On JobSeeker	0.058	0.316	1.059 (0.570, 1.967)	0.855
Lagged health score	-	0.014	0.005	1.014 (1.004, 1.025)	0.008 ***
Lagged income	-	0.223	0.125	1.250 (0.979, 1.595)	0.073 *
Capacity to work (relative to full capacity to work)	Partial capacity to work	-1.214	0.769	0.297 (0.066, 1.340)	0.114

1 Wave 17 is used for all health models (GP visits, health declines and hospitalisations) due to COVID effects in Wave 21
2 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level
The GP visits model has a multiclass AUC of 0.70.

GP visits multinomial model: Two to four GP visits per year relative to none

HILDA Wave 17 | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,883* | *Multinomial regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[1]
Intercept	-	-1.381	0.835	0.251 (0.049, 1.292)	0.098 *
Gender (relative to female)	Male	-0.458	0.140	0.633 (0.481, 0.833)	0.001 **
Whether living with partner (relative to living with partner)	Not living with partner	-0.164	0.159	0.849 (0.621, 1.160)	0.302
Age bands (relative to 18 to 21 years old)	22 to 25 years old	0.934	0.335	2.546 (1.321, 4.904)	0.005 ***
	26 to 35 years old	0.831	0.293	2.296 (1.293, 4.075)	0.005 ***
	36 to 44 years old	0.638	0.336	1.893 (0.980, 3.657)	0.057 *
	45 to 55 years old	0.288	0.286	1.334 (0.761, 2.337)	0.315
	56 to 66 years old	1.522	0.292	4.582 (2.586, 8.119)	1.83×10^{-7} ***
Current JobSeeker status (relative to not on JobSeeker)	On JobSeeker	-0.075	0.224	0.927 (0.598, 1.437)	0.736
Lagged health score	-	-0.006	0.004	0.994 (0.987, 1.001)	0.074 *
Logged income	-	0.222	0.083	1.248 (1.060, 1.470)	0.008 **
Capacity to work (relative to full capacity to work)	Partial capacity to work	0.356	0.320	1.428 (0.762, 2.675)	0.266

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level
The GP visits model has a multiclass AUC of 0.70.

GP visits multinomial model: Five to seven GP visits per year relative to none

HILDA Wave 17 | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,883* | *Multinomial regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[1]
Intercept	-	-1.351	1.015	0.259 (0.035, 1.895)	0.183358
Gender (relative to female)	Male	-0.814	0.159	0.443 (0.325, 0.605)	3.04×10^{-7} ***
Whether living with partner (relative to living with partner)	Not living with partner	-0.235	0.177	0.790 (0.559, 1.117)	0.183
Age bands (relative to 18 to 21 years old)	22 to 25 years old	1.07	0.396	2.917 (1.341, 6.345)	0.007 ***
	26 to 35 years old	0.371	0.368	1.450 (0.705, 2.981)	0.312
	36 to 44 years old	0.156	0.429	1.168 (0.504, 2.711)	0.717
	45 to 55 years old	-0.047	0.358	0.954 (0.473, 1.927)	0.896
	56 to 66 years old	1.195	0.348	3.304 (1.669, 6.542)	0.001 ***
Current JobSeeker status (relative to not on JobSeeker)	On JobSeeker	0.047	0.265	1.048 (0.623, 1.762)	0.860
Lagged health score	-	-0.022	0.004	0.978 (0.971, 0.986)	2.96×10^{-8} ***
Logged income	-	0.272	0.102	1.313 (1.074, 1.604)	0.008 ***
Capacity to work (relative to full capacity to work)	Partial capacity to work	0.457	0.356	1.579 (0.786, 3.175)	0.200

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level
The GP visits model has a multiclass AUC of 0.70.

GP visits multinomial model: More than 8 GP visits per year relative to none

HILDA Wave 17 | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,883* | *Multinomial regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[1]
Intercept	-	1.788	0.889	5.979 (1.047, 34.129)	0.044 **
Gender (relative to female)	Male	-0.823	0.15	0.439 (0.327, 0.589)	4.28×10^{-8} ***
Whether living with partner (relative to living with partner)	Not living with partner	-0.149	0.168	0.861 (0.620, 1.197)	0.375
Age bands (relative to 18 to 21 years old)	22 to 25 years old	0.779	0.376	2.180 (1.043, 4.558)	0.038 **
	26 to 35 years old	0.213	0.332	1.237 (0.646, 2.371)	0.521
	36 to 44 years old	0.081	0.384	1.085 (0.511, 2.301)	0.832
	45 to 55 years old	-0.221	0.317	0.802 (0.431, 1.491)	0.485
	56 to 66 years old	1.059	0.315	2.884 (1.554, 5.351)	0.001 ***
Current JobSeeker status (relative to not on JobSeeker)	On JobSeeker	-0.085	0.242	0.918 (0.572, 1.475)	0.724
Lagged health score	-	-0.047	0.004	0.954 (0.947, 0.961)	$< 2.0 \times 10^{-16}$ ***
Logged income	-	0.152	0.090	1.164 (0.976, 1.388)	0.092 *
Capacity to work (relative to full capacity to work)	Partial capacity to work	1.205	0.312	3.337 (1.810, 6.150)	1.00×10^{-4} ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level
The GP visits model has a multiclass AUC of 0.70.

GP visits and the likelihood of experiencing a health decline have a non-linear relationship, likely reflecting other health confounders

HILDA Wave 17 | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,883* | *Logistic regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[1]
Intercept	-	-2.248	0.269	0.106 (0.062, 0.179)	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	0.021	0.082	1.022 (0.871, 1.199)	0.292
Age bands (relative to 18 to 21 years old)	22 to 25 years old	0.178	0.236	1.195 (0.752, 1.899)	0.451
	26 to 35 years old	0.106	0.214	1.112 (0.731, 1.691)	0.620
	36 to 44 years old	-0.139	0.249	0.87 (0.535, 1.416)	0.577
	45 to 55 years old	-0.116	0.215	0.89 (0.585, 1.356)	0.590
	56 to 66 years old	0	0.202	1 (0.673, 1.485)	1
Current labour force status (relative to working part time)	Working full time	0.106	0.166	1.112 (0.803, 1.54)	0.523
	Looking for full time work	0.273	0.227	1.314 (0.843, 2.049)	0.229
	Looking for part time work	-0.028	0.383	0.972 (0.459, 2.061)	0.942
	Not in LF – marginally associated	0.378	0.133	1.245 (0.889, 1.744)	0.203
	Not in LF – not associated	0.378	0.133	1.46 (1.125, 1.894)	0.004 ***
Number of GP visits (relative to none)	1 visit	-0.487	0.206	0.615 (0.41, 0.921)	0.018 **
	2 to 4 visits	-0.278	0.146	0.757 (0.568, 1.009)	0.057 *
	5 to 7 visits	0.062	0.164	1.063 (0.771, 1.467)	0.705
	Over 8 visits	0.579	0.158	1.785 (1.308, 2.434)	2.48×10^{-4} ***
Whether on JobSeeker (relative to not on JobSeeker)	On JobSeeker	0.186	0.155	1.205 (0.889, 1.633)	0.230
Previous year's health score	-	0.026	0.002	1.027 (1.023, 1.031)	$< 2.0 \times 10^{-16}$ ***
Capacity to work (relative to full capacity to work)	Partial capacity to work	0.353	0.582	1.424 (0.455, 4.454)	0.544
Number of GP visits x Capacity to work (relative to full capacity to work)	1 visit x Partial	-	-	-	-
	2 to 4 visits x Partial	0.452	0.658	1.571 (0.433, 5.703)	0.492
	5 to 7 visits x Partial	-0.344	0.719	0.709 (0.173, 2.899)	0.632
	Over 8 visits x Partial	-0.247	0.613	0.781 (0.235, 2.597)	0.687

[1] Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
The Health decline model has an AUC of 0.65, suggesting there is high variance that is not captured; however, this model shows that health has a neutral association with income.

Hospital admissions are modelled through the health score of comparable low-income households

HILDA Wave 17 | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,882* | *Logistic regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[1]
Intercept	-	-2.1	0.385	0.122 (0.057, 0.261)	4.90983E-08
Age bands (relative to 18 to 21 years old)	Under 18 years old	0.048	0.713	1.049 (0.259, 4.241)	0.946
	22 to 25 years old	-0.272	0.358	0.762 (0.378, 1.536)	0.447
	26 to 35 years old	-0.149	0.308	0.861 (0.471, 1.575)	0.629
	36 to 44 years old	-0.301	0.358	0.74 (0.367, 1.494)	0.400
	45 to 55 years old	-0.158	0.303	0.854 (0.471, 1.547)	0.602
	56 to 66 years old	-0.2	0.285	0.819 (0.469, 1.431)	0.483
	67 to 76 years old	-0.06	0.284	0.942 (0.54, 1.642)	0.833
	77 years and above	0.307	0.287	1.359 (0.775, 2.383)	0.285
Gender (relative to Female)	Male	-0.085	0.105	0.918 (0.748, 1.127)	0.418
Current labour force status (relative to working part time)	Employed - full time	0.277	0.279	1.319 (0.763, 2.28)	0.321
	Unemployed – looking for full time work	0.514	0.319	1.673 (0.895, 3.125)	0.107
	Unemployed – looking for part time work	1.031	0.454	2.804 (1.153, 6.821)	0.023 **
	Not in LF – marginally associated	0.695	0.24	2.003 (1.252, 3.203)	0.004 ***
	Not in LF – not associated	0.66	0.198	1.935 (1.313, 2.85)	8.54×10^{-4} ****
Current JobSeeker status (relative to not on JobSeeker)	On JobSeeker	0.25	0.201	1.284 (0.866, 1.903)	0.214
Health score	-	-0.01	0.002	0.99 (0.986, 0.995)	5.73×10^{-7} ***

Continued on next page

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
The hospital admissions model has an AUC: 0.73.

Hospital admissions are modelled through the health score of comparable low-income households, continued

HILDA Wave 17 | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 2,882* | *Logistic regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO	P-VALUE[1]
Continued from previous page					
Number of GP visits (relative to none)	1 visit	-0.367	0.395	0.693 (0.319, 1.503)	0.353
	2 to 4 visits	0.048	0.249	1.049 (0.643, 1.71)	0.847
	5-7 visits	0.73	0.256	2.075 (1.257, 3.425)	0.004 ***
	Over 8 visits	1.33	0.244	3.78 (2.342, 6.101)	5.01×10^{-8} ***
Capacity to work (relative to full capacity to work)	Partial capacity to work	0.61	0.696	1.841 (0.47, 7.204)	0.381
Number of GP visits x Full capacity to work	1 visit x Partial	2.377	1.726	10.767 (0.366, 317.166)	0.168
	2 to 4 visits x Partial	0.413	0.783	1.512 (0.326, 7.013)	0.598
	5-7 visits x Partial	-1.142	0.934	0.319 (0.051, 1.993)	0.221
	Over 8 visits x Partial	-1.024	0.726	0.359 (0.087, 1.489)	0.1584

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
The hospital admissions model has an AUC: 0.73.

Financial stress is modelled using comparable low-income households, and the associations between income and being under financial stress

All HILDA waves | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 63,737* | *Logistic regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	-0.038	0.411	0.963 (0.43, 2.155)	0.926
Age (relative to 45 to 66 year olds)	26 to 44 year olds	0.737	0.04	2.09 (1.933, 2.259)	$< 2.0 \times 10^{-16}$ ***
	22 to 25 year olds	0.558	0.055	1.747 (1.569, 1.945)	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	-0.031	0.032	0.969 (0.91, 1.032)	0.333
Living with partner (relative to living with partner)	Not living with partner	0.506	0.036	1.659 (1.546, 1.782)	$< 2.0 \times 10^{-16}$ ***
Children (relative to has dependent child aged less than 15 years)	Has dependent child over 15 years old	0.064	0.092	1.066 (0.89, 1.276)	0.487
	Has independent child	-0.011	0.091	0.989 (0.828, 1.181)	0.904
	No children	-0.532	0.041	0.587 (0.542, 0.637)	$< 2.0 \times 10^{-16}$ ***
Highest educational attainment (relative to high school)	Did not complete high school	0.056	0.045	1.057 (0.968, 1.154)	0.213
	Certificate or diploma	0.268	0.045	1.308 (1.196, 1.429)	2.59×10^{-9} ***
	Bachelors or higher	-0.189	0.060	0.828 (0.736, 0.932)	0.002 ***
Labour force status (relative to employed - part time)	Employed - full time	-0.115	0.048	0.891 (0.811, 0.979)	0.017 **
	Unemployed – looking for full time work	0.584	0.066	1.794 (1.578, 2.04)	$< 2.0 \times 10^{-16}$ ***
	Unemployed – looking for part time work	0.533	0.095	1.704 (1.414, 2.053)	2.07×10^{-8} ***
	Not in LF – marginally associated	0.591	0.05	1.806 (1.636, 1.993)	$< 2.0 \times 10^{-16}$ ***
	Not in LF – not associated	0.217	0.046	1.243 (1.136, 1.359)	2.39×10^{-6} ***
On JobSeeker (relative to not on JobSeeker)	On JobSeeker	0.530	0.044	1.698 (1.558, 1.85)	$< 2.0 \times 10^{-16}$ ***
Logged income	-	-0.251	0.040	0.778 (0.719, 0.842)	3.50×10^{-10} ***
COVID dummy (relative to non-COVID)	COVID year	-0.065	0.061	0.937 (0.831, 1.057)	0.267

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level
The financial stress model has an AUC of 0.78.

Psychological distress is modelled using the link between financial stress and income of the low-income households

All HILDA waves | *Excludes individuals with earnings or combined household income greater than $50,000* | *n = 21,287* | *Linear regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	1.411	0.035	-	$< 2.0 \times 10^{-16}$ ***
Age (relative to 45 to 66 year olds)	26 to 44 year olds	0.297	0.022	-	$< 2.0 \times 10^{-16}$ ***
	22 to 25 year olds	0.236	0.029	-	4.4×10^{-16} ***
Gender (relative to Female)	Male	-0.007	0.013	-	0.59
Living with partner (relative to living with partner)	Not living with partner	0.085	0.014	-	1.27×10^{-9} ***
Children (relative to has dependent child aged less than 15 years)	Has dependent child over 15 years old	0.242	0.057	-	2.18×10^{-5} ***
	Has independent child	0.256	0.046	-	2.62×10^{-8} ***
	No children	0.123	0.025	-	8.65×10^{-7} ***
Highest educational attainment (relative to high school)	Did not complete high school	0.044	0.021	-	0.036 **
	Certificate or diploma	-0.026	0.021	-	0.216
	Bachelors or higher	-0.112	0.025	-	7.46×10^{-6} ***
Labour force status (relative to employed - part time)	Employed - full time	-0.185	0.024	-	$1.27 * x10^{-14}$ ***
	Unemployed – looking for full time work	0.307	0.042	-	2.68×10^{-13} ***
	Unemployed – looking for part time work	0.304	0.058	-	1.59×10^{-7} ***
	Not in LF – marginally associated	0.408	0.028	-	$< 2.0 \times 10^{-16}$ ***
	Not in LF – not associated	0.332	0.021	-	$< 2.0 \times 10^{-16}$ ***
On JobSeeker (relative to not on JobSeeker)	On JobSeeker	0.159	0.027	-	3.89×10^{-9} ***
Under financial stress (relative to not under financial stress)	Under financial stress	0.675	0.022	-	$< 2.0 \times 10^{-16}$ ***
COVID dummy (relative to non-COVID)	COVID year	0.194	0.021	-	$< 2.0 \times 10^{-16}$ ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
As the psychological distress model is a linear regression, we measure the goodness of fit using the R-squared. For the psychological distress model, the R squared is 0.22.

The modelling of the psychological distress provides a pathway to measuring the change in the JobSeekers' Quality Adjusted Life Years

HILDA Wave 17 | *All individuals with health weights* | *n = 14,723* | *Linear regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	0.929	0.004	-	$< 2.0 \times 10^{-16}$ ***
Age bands (relative to 18 to 21 years old)	22 to 25 years old	-0.003	0.004	-	0.453
	26 to 35 years old	-0.02	0.004	-	5.73×10^{-7} ***
	36 to 44 years old	-0.032	0.004	-	1.33×10^{-15} ***
	45 to 55 years old	-0.049	0.004	-	$< 2.0 \times 10^{-16}$ ***
	56 to 66 years old	-0.066	0.004	-	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	0.013	0.002	-	8.03×10^{-11} ***
Highest educational attainment (relative to high school)	Did not complete high school	0.013	0.002	-	0.008 ***
	Certificate or diploma	-0.004	0.003	-	0.182
	Bachelors or higher	0.007	0.003	-	0.020 **
On JobSeeker (relative to not on JobSeeker)	On JobSeeker	-0.022	0.004	-	3.89×10^{-8} ***
Psychological distress score	-	-0.084	0.001	-	$< 2.0 \times 10^{-16}$ ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
As the Quality Adjusted Life Years (QALY) model is a linear regression, we measure the goodness of fit using the R-squared. For the psychological distress model, the R squared is 0.43.

The year 9 NAPLAN reading scores for children of JobSeekers in the microsimulation are modelled using their parent's average income

All LSAC Waves | *All individuals with Year 9 NAPLAN reading scores* | *n = 4,293* | *Linear regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	400.43	24.982	-	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	-14.226	1.944	-	2.58×10^{-13} ***
Parent's highest educational attainment (relative to high school)	Did not complete high school	-12.662	4.375	-	0.004 ***
	Certificate or diploma	0.986	4.270	-	0.816
	Bachelors or higher	27.780	4.142	-	1.89×10^{-11} ***
Proportion of childhood where parents were on income support	-	-15.171	13.924		0.307
Logged parent's average income over childhood	-	17.475	2.171	-	3.33×10^{-15} ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
The year 12 NAPLAN reading score model has an R-squared of 0.14.

Similarly, the year 9 numeracy scores of children of the JobSeekers in the microsimulation are modelled using their parent's average income

All LSAC Waves | *All individuals with Year 9 NAPLAN numeracy scores* | *n = 4,257* | *Linear regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	360.533	24.939	-	$< 2.0 \times 10^{-16}$ ***
Gender (relative to Female)	Male	12.789	1.95	-	5.38×10^{-11} ***
Parent's highest educational attainment (relative to high school)	Did not complete high school	-14.438	4.402	-	0.001 ***
	Certificate or diploma	-4.006	4.293	-	0.351
	Bachelors or higher	21.143	4.165	-	3.85×10^{-7} ***
Proportion of childhood where parents were on income support	-	-24.048	14.042		0.087 *
Logged parent's average income over childhood	-	20.929	2.167	-	$< 2.0 \times 10^{-16}$ ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
The year 12 NAPLAN numeracy score model has an R-squared of 0.14.

The child's year 9 NAPLAN scores are then used to model whether the child completes year 12 or not

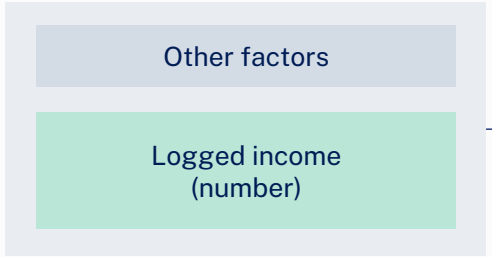
LSAY 2015 cohort | *All individuals with year 9 reading and numeracy NAPLAN scores and year 12 outcomes* | *n = 3,501* | *Logistic regression*

VARIABLE	CATEGORY	COEFFICIENT	STD ERROR	ODDS-RATIO (95% CI)	P-VALUE[1]
Intercept	-	0.87	0.231	2.386 (1.516, 3.755)	1.66×10^{-4} ***
Gender (relative to Female)	Male	-0.553	0.142	0.575 (0.435, 0.760)	9.85×10^{-5} ***
Parent's highest educational attainment (relative to high school)	Did not complete high school	-0.580	0.240	0.560 (0.350, 0.896)	0.016 **
	Certificate or diploma	0.102	0.223	1.108 (0.715, 1.716)	0.647
	Bachelors or higher	0.499	0.166	1.647 (1.190, 2.280)	0.003 ***
Average year 9 NAPLAN score (average of reading and numeracy NAPLAN scores)	-	0.003	0	1.003 (1.003, 1.004)	$< 2.0 \times 10^{-16}$ ***

1 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.
The year 12 completion model has an AUC of 0.71.

The increase to JobSeeker will reduce the number of JobSeekers that are under financial stress and reduce their level of psychological distress

FINANCIAL STRESS AND PSYCHOLOGICAL DISTRESS MODELLING IN THE MICROSIMULATION

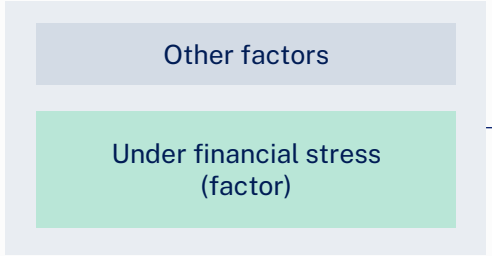


E

Under financial stress[1] (factor)

FINANCIAL STRESS FACTORS	COEFFICIENT	P-VALUE[3]
Logged income	-0.251	3.50×10^{-10} ***

Description of results: A 1-point increase in the logged income of an individual is associated with that individual being 0.778 as likely to be under financial stress as an individual without an increase in logged income ($p = 3.50 \times 10^{-10}$).



F

Psychological distress score[2] (factor)

PSYCHOLOGICAL DISTRESS SCORE FACTORS	COEFFICIENT	P-VALUE
Under financial stress (relative to not under financial stress)	0.675	$< 2.0 \times 10^{-16}$ ***

Description of results: Being under financial stress is associated with an additional 0.675 points in their psychological distress score ($p=3.50 \times 10^{-10}$), which effectively moves them up n entire Kesseler 10 risk category (for example from 2 – moderate psychological distress to 3 – high psychological distress).

Rules based variable
Exogenous variable
Endogenous variable

1 Financial stress is modelled using 6 of the 7 financial stress questions asked in HILDA and if the individuals answer yes to three or more of these questions. The 7th question, whether accessing welfare, is removed to reduce leakage between the dependent and response variable.
2 Psychological distress is modelled based on the grouped K10 scores of psychological distress (risk categories): 1 – Low, 2 – Moderate, 3 – High, 4 – Very high.
3 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Decreasing the level of psychological distress improves JobSeekers' Quality Adjusted Life Years (QALYs)

PSCYHOLOGICAL DISTRESS AND QUALITY ADJUSTED LIFE YEARS MODELLING IN THE MICROSIMULATION

QUALITY ADJUSTED LIFE YEARS FACTORS	COEFFICIENT	P-VALUE[2]
Psychological distress score	-0.084	$< 2.0 \times 10^{-16}$ ***

Description of results: Quality Adjusted Life Years are measured from 0 to 1, where 1 represents a full year. A 1-point increase in the level of psychological distress of JobSeekers (measured through the risk categories) is associated with a 0.084 decrease in an individual's Quality Adjusted Life Years ($p < 2.0 \times 10^{-16}$).

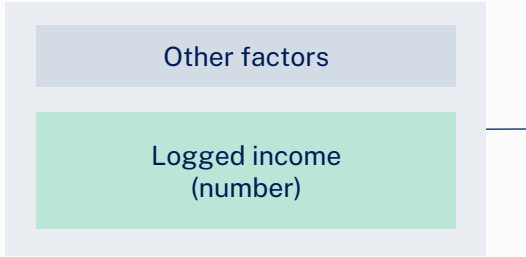
Rules based variable
Exogenous variable
Endogenous variable
Output

1 Quality Adjusted Life Years is modelled using the SF-6D health state classification HILDA variable (ghsf6d). The effect of an illness on quality of life is reflected by a 'utility weight' (derived from standard valuations), where a weight of 1 equates to perfect health, and a weight of 0 is equated with death. This methodology is comparable to the methodology applied in the Productivity Commission's (2020) *Mental Health Inquiry*, see Box I.2.

[2] Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

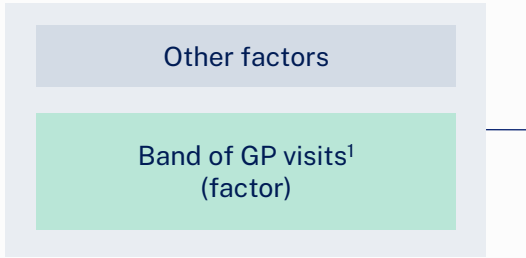
The increase to JobSeeker will increase the likelihood of JobSeekers visiting the GP more frequently, but the effect on experiencing a health decline is non-linear

HEALTH MODELLING IN THE MICROSIMULATION



OUTCOME BAND OF GP VISITS (RELATIVE TO NONE)	LOGGED INCOME COEFFICIENT	P-VALUE[2]
1 visit	0.223	0.1143
2 – 4 visits	0.222	0.0077 ***
5 – 7 visits	0.272	0.0033 ***
Over 8 visits	0.1510	0.0916 *

Description of results: The relationship between logged income and GP visits is modelled logistically. A 1 point increase logged income is associated with increased odds of being in the 1 visit bucket by 1.250 (p=0.1143, not significant), in the 2-4 visit bucket by 1.248 (p=0.0077), the 5-7 visit bucket by 1.313 (p=0.0033), and the over 8 visits bucket by 1.164 (p=0.0916), all relative to having no GP visits.



HEALTH DECLINE FACTORS	COEFFICIENT	P-VALUE
1 visit (relative to None)	-0.487	0.0181 **
2 – 4 visits (relative to None)	-0.278	0.0569 **
5 – 7 visits (relative to None)	0.062	0.7054
Over 8 visits (relative to None)	0.579	0.0002 ***

Description of results: The relationship between GP visits and health decline is modelled using a binary logistic regression. Compared to having no GP visits, those who have 1 GP visit are 0.615 times as likely to experience health decline (p=0.0129), those with 2-4 GP visits are 0.568 times as likely to experience a health decline (p=0.0783), those with 5-7 GP visits are 0.709 times as likely to experience a health decline though this is not statistically significant (p=0.7557), and those with over 8 visits is are 1.785 times as likely to experience a health decline (p=0.0002). GP visits are modelled using bands due to the non-linear relationship between GP visits and experiencing a health decline. Even when controlling for long-term health conditions this relationship is still observed.

1 The band of GP visits are used instead of the number of GP visits as there is a nonlinear relationship between GP visits and the likelihood of experiencing health decline.
2 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

A higher health score (indicating better health) will reduce the likelihood of an individual being admitted to hospital during the year

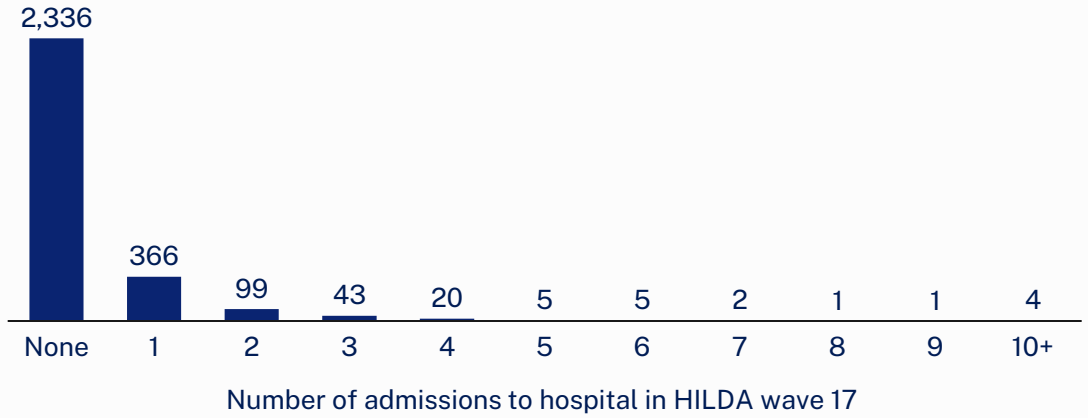
HEALTH MODELLING IN THE MICROSIMULATION

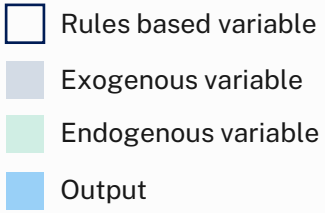
HOSPITAL ADMISSION FACTORS	HEALTH SCORE COEFFICIENT	P-VALUE[2]
Health score	-0.0105	5.73×10^{-7} ***

Description of results: The relationship between physical health and whether being admitted to a hospital is modelled logistically. Here, a 1-point increase in the health score of an individual reduces their odds of being admitted to hospital by 0.99 ($p = 5.73 \times 10^{-7}$).

A note on modelling: Whether someone is admitted to hospital during that year, a binary outcome, is modelled instead of the number of hospitalisations due to the right skew present in the HILDA hospitalisations data.

Therefore, a model that predicted the number of admissions would likely perform poorly. A linear model that predicts the number of hospitalisations produced an R squared of 0.04.

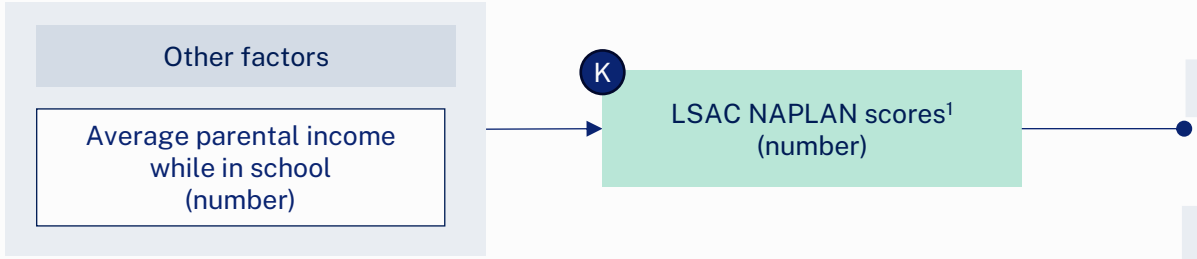




1 Whether admitted to hospital or not during the year is used rather than a total number as the distribution of number of hospital admissions is right skewed (not many hospital admission). The binary outcome of whether being admitted or not also produces a better fit.
2 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

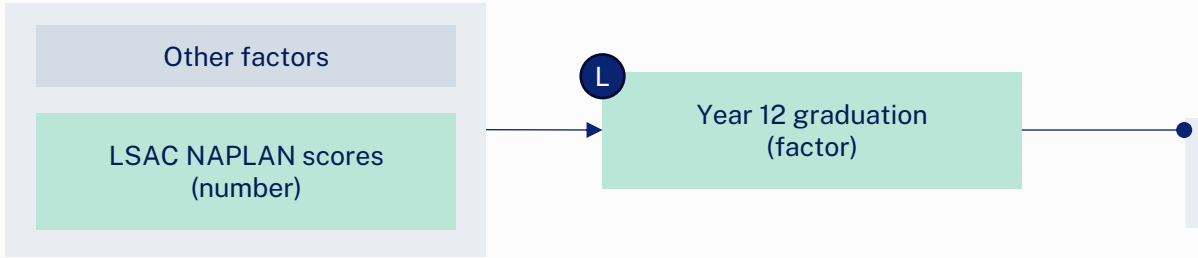
The increase to JobSeeker will improve NAPLAN scores of children of JobSeekers which will improve their likelihood of completing year 12

CHILDHOOD DEVELOPMENT MODELLING IN THE MICROSIMULATION



READING NAPLAN SCORE FACTORS	COEFFICIENT	P-VALUE[2]
Logged average income	17.293	3.33×10^{-15} ***
NUMERACY NAPLAN SCORE FACTORS	**COEFFICIENT**	**P-VALUE**
Logged average income	20.994	$< 2.0 \times 10^{-16}$ ***

Description of results: A 1-point increase in the parent's logged average income is associated with an increase in the child's year 9 NAPLAN reading score by 17 points ($p=3.33 \times 10^{-15}$) and an increase in the child's year 9 NAPLAN numeracy score by 21 points ($p< 2.0 \times 10^{-16}$).



YEAR 12 COMPLETION FACTORS	COEFFICIENT	P-VALUE
Average NAPLAN score (average of reading and numeracy scores)	0.003	$< 2.0 \times 10^{-16}$ ***

Description of results: A 1-point increase in a child's average year 9 NAPLAN score (average of reading and numeracy) is 1.003 times as likely to complete year 12 as a child who does not see an increase in their average year 9 NAPLAN score. This indicates that a higher year 9 NALPAN score is associated with a higher likelihood to complete year 12.

Rules based variable
Exogenous variable
Endogenous variable
Output

1 LSAC year 9 NAPLAN reading and numeracy scores are modelled separately.
2 Statistical significance: *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

We use a 7% real discount rate to value future costs and benefits in today's dollars

DISCOUNT RATE AND PRESENT VALUE METHODOLOGY

Overview: The microsimulation produces values in constant prices (no inflation or growth adjustments). Therefore, we apply a real discount rate directly to these values.

- The microsimulation results are calculated in constant prices

- The HILDA regression coefficients represent relationships between variables at a point in time
- When applying these coefficients in the microsimulation, we don't inflate values over time
- No wage growth, price inflation, or benefit indexation is applied to future years
- Cost assumptions and other monetary values stay constant in the simulation

- Converting to 2024 dollars

- We use a real discount rate of 7% per annum, as:
  - The values from the microsimulation are in constant dollars
  - 7% is the standard real discount rate per Australian Government guidelines
  - No adjustment for inflation or GDP growth is needed since the microsimulation values don't include these factors

Sensitivity analysis: To test robustness we use a lower bound of 3% real rate and an upper bound of 10% real rate.

Rationale: The 7% base rate balances the opportunity cost of capital in the private sector, social time preferences for consumption and risk premiums for public investments.[1]

Formula:

$$PV = \sum_{t=1}^{10} \frac{(B_t - C_t)}{(1+r)^t}$$

Where:

- PV = Present value in 2024 dollars
- B_t = Benefits in year t
- C_t = Costs in year t
- r = Real discount rate (7% base case)
- t = Year (1 to 10, where 1 is 2025)

1 As per Office of Best Practice Regulation (OBPR) (2021) *Cost-Benefit Analysis Guidelines.* All costs have been discounted with either 3%, 7% or 10% depending on the scenario. The only exception is the lifetime social security costs, which are discounted at 5% across all scenarios as these costs have been informed by the Priority Investment Approach, which applies a 5% discount rate.
Source: Mandala analysis.

Costs for the microsimulation are derived from previous reviews of Government services and public costs

TABLE OF COST INPUTS

CATEGORY	ITEM	COST (AUD)	SOURCE
JobSeeker payments[1]	JobSeeker payments	*Varies*	Services Australia (2024) payment rates data
Health	GP consult	$64.20	Medicare Benefits Schedule (2024). Combining rebates for Item 23 and Item 75870. Medicare Benefits Schedule - Item 23: Professional attendance by a general practitioner at consulting rooms lasting at least 6 minutes and less than 20 minutes. Medicare Benefits Schedule - Item 75870: Bulk-Billing incentive item when attendance service is provided to a patient who is a concessional beneficiary.
	Hospital admission	$5,824	Taylor Fry (2021) *Pathways to Homelessness*. Cost of Hospital Admission per event (separation) was $5,030 in 2020 according to the Independent Pricing Hospital Authority 2016/17 for NSW.
	Cost of suicide	$9,400,000	Productivity Commission (2020) *Mental Health Inquiry* estimates of the average cost of a life lost to suicide in 2018 for an unemployed Australian. See Table H.8 for more details.
Quality adjusted life years	Quality adjusted life years	$79,000	$79,000 per one QALY in 2023 dollars, scaled for inflation from Huang et al.'s (2018) *Life satisfaction, QALYs, and the monetary value of health* estimate that individual's willingness to pay for one QALY is approximately A$42,000-A$67,000.
Children's lifetime social security cost[2]	Completed year 12, spent under 50% of time with parent receiving income support	$225,000	Supplied by Australian Priority Investment Approach to Welfare – lifetime social security costs
	Completed year 12, spent over 50% of time with parent receiving income support	$312,000	Supplied by Australian Priority Investment Approach to Welfare – lifetime social security costs
	Did not complete year 12, spent under 50% of time with parent receiving income support	$257,000	Supplied by Australian Priority Investment Approach to Welfare – lifetime social security costs
	Did not complete year 12, spent over 50% of time with parent receiving income support	$409,000	Supplied by Australian Priority Investment Approach to Welfare – lifetime social security costs
Children's lifetime earnings differential	Completed year 12 compared to those who did not complete	$277,120	Department of Education (2024) *Multi-Agency Data Integration Project 2016*. In 2016, those who completed Year 11 or below had a median income from wages and salaries of $38,281. For those who complete Year 12 it was $43,967. To be conservative, we do not make assumptions about the proportion who may complete further qualifications. We inflate by the Wage Price Index to 2024. The difference in wages is held constant over a 40-year working life span.

1 JobSeeker payments are determined for each individual in the representative cohort using the eligibility criteria provided by Services Australia
2 Lifetime social security costs for children are calculated based on parameters supplied by the Australian Priority Investment Approach to Welfare modelling team; depending on a child's completion of year 12 and the extent that a parent receiving income support.

Costs of suicides are calculated using the AIHW suicide rates adjusted by level of psychological distress using incident rate ratios from the literature

MODELLING COSTS OF SUICIDES

PSYCHOLOGICAL DISTRESS SCORE ADJUSTED SUICIDE RATES

Suicide rate for individuals **by whether receiving JobSeeker**[1] (number) × Psychological distress IRR[2] (number) = Suicide rate for individuals **by whether receiving JobSeeker** and **by K10 risk category** (number)

DIFFERENCE IN SUICIDES PER YEAR

Suicide rate for individuals not on JobSeeker by K10 risk category (number) × [**Baseline:** Number of individuals not on JobSeeker by K10 risk category per year (number) − **Shock:** Number of individuals not on JobSeeker by K10 risk category per year (number)] = Difference in non-JobSeeker suicides per year (number)

Suicide rate for individuals on JobSeeker by K10 risk category (number) × [**Baseline:** Number of individuals not on JobSeeker by K10 risk category per year (number) − **Shock:** Number of individuals not on JobSeeker by K10 risk category per year (number)] = Difference in JobSeeker suicides per year (number)

Rules based variable

Output

1 AIHW, Age-standardised rates of suicide among those who received income support payments 2019 (2022)
2 Erlangsen et al. (2021) Measures of mental, physical, and social wellbeing and their association with death by suicide and self-harm in a cohort of 266,324 persons aged 45 years and over. Soc Psychiatry Epidemiol 56, 295–303. https://doi.org/10.1007/s00127-020-01929-2

Costs of suicides are calculated using the AIHW suicide rates adjusted by level of psychological distress using incident rate ratios from the literature, continued

MODELLING COSTS OF SUICIDES

TOTAL DIFFERENCE IN SUICIDES

$$\sum \left[\text{Difference in non-JobSeeker suicides per year (number)} + \text{Difference in JobSeeker suicides per year (number)} \right] = \text{Total difference in suicides across the representative cohort in all years (number)}$$

TOTAL COST OF SUICIDES

$$\text{Total difference in suicides across the representative cohort in all years (number)} \times \text{Cost of suicide}^{1} \text{ (number)} = \text{Total difference in cost of suicides (number)}$$

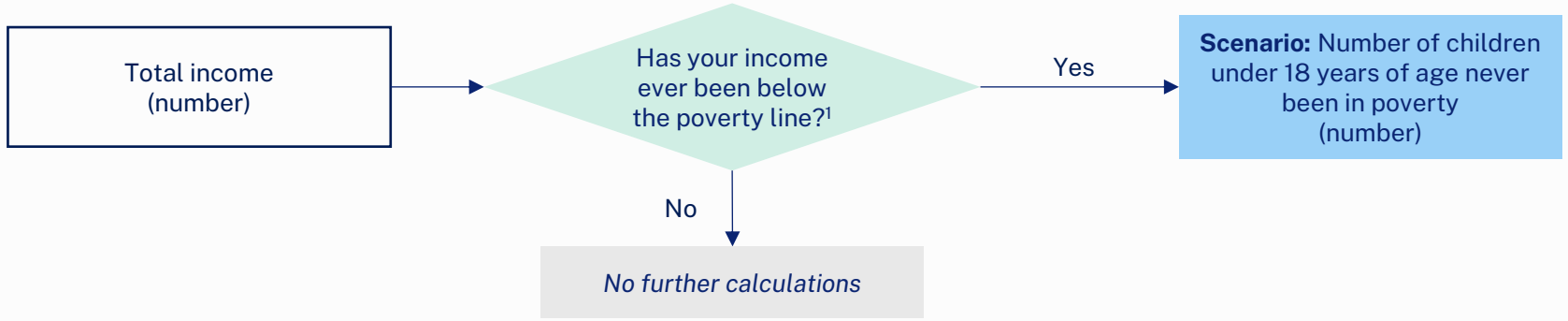
- Rules based variable
- Exogenous variable
- Endogenous variable
- Output

1 Cost of suicide $9.4million AUD, based on Productivity Commission (2020) estimates of the average cost of a life lost to suicide in 2018 for an unemployed Australian. See Table H.8.

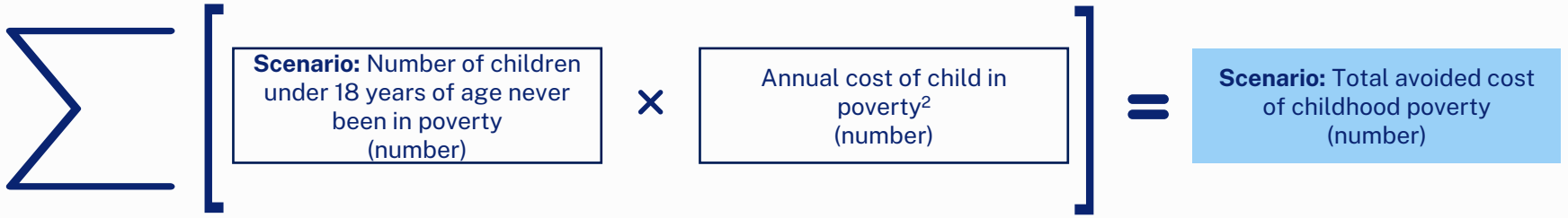
The benefit of added disability adjusted life years of children is calculated through the number of children of JobSeekers who would not experience poverty

MODELLING COST OF CHILDHOOD POVERTY

CHILDREN LIVING IN POVERTY



TOTAL COST OF CHILDHOOD POVERTY OF SCENARIO

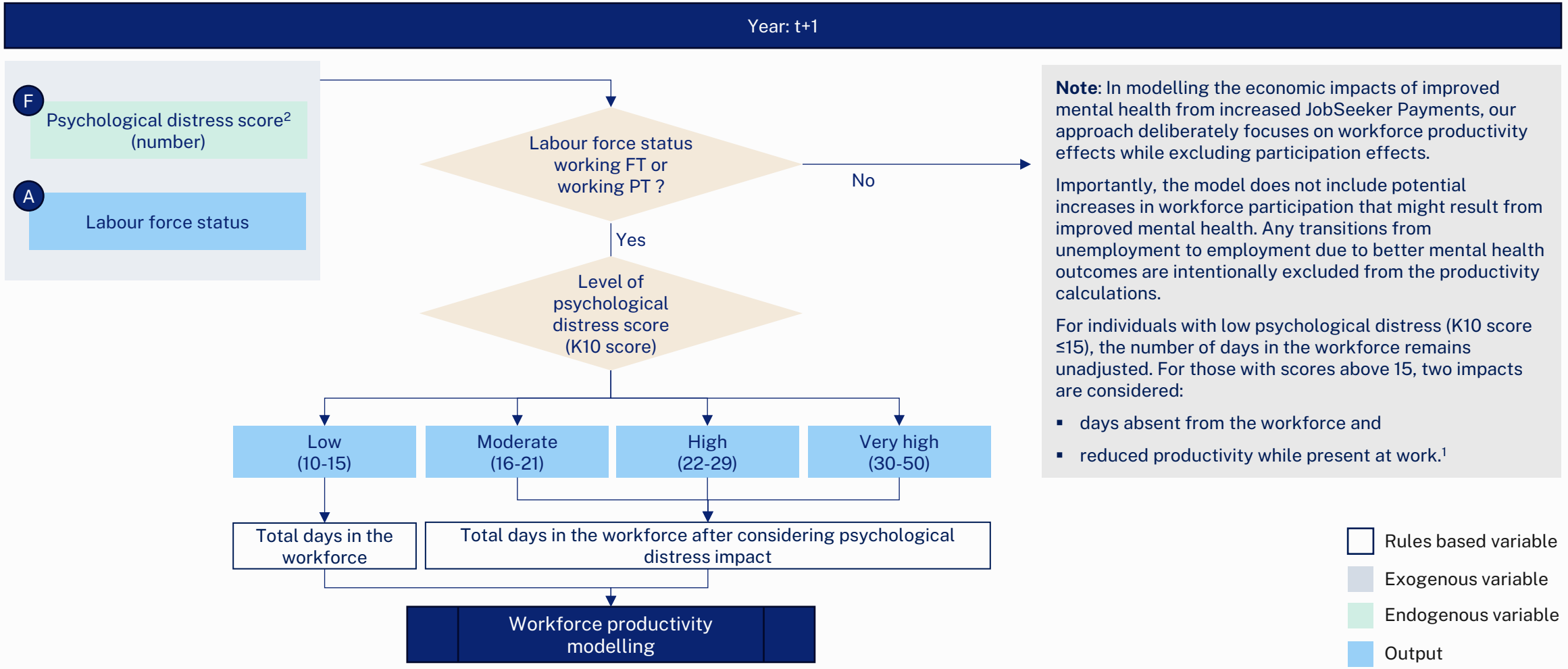


Rules based variable
Exogenous variable
Endogenous variable
Output

1 The poverty line is determined from the weekly income of an individual and their family circumstances in correspondence with the Melbourne Institute's most recent publication of the Australian poverty lines. Source: Melbourne Institute: Applied Economics and Social Research, Poverty Lines : Australia, March Quarter 2024 (2024)
2 The annual cost of poverty is calculated based off the annual lost DALYs due to poor health and excludes the labour market outcomes and government services numbers to ensure no double counting of benefits. Source: NCOSS and Impact Economics and Policy, Lasting Impacts: The Economic Costs of Child Poverty in New South Wales (2024)

We identify the psychological distress levels of those who re-join the workforce in both scenarios

SEGMENTING WORKFORCE RE-JOINERS BY PSYCHOLOGICAL DISTRESS



Note: In modelling the economic impacts of improved mental health from increased JobSeeker Payments, our approach deliberately focuses on workforce productivity effects while excluding participation effects.

Importantly, the model does not include potential increases in workforce participation that might result from improved mental health. Any transitions from unemployment to employment due to better mental health outcomes are intentionally excluded from the productivity calculations.

For individuals with low psychological distress (K10 score ≤15), the number of days in the workforce remains unadjusted. For those with scores above 15, two impacts are considered:

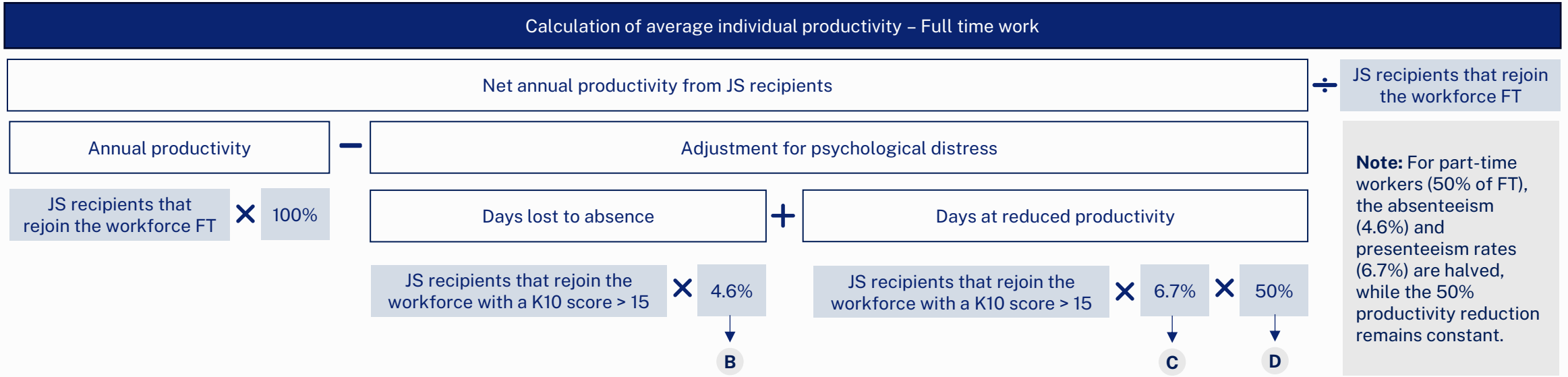
- days absent from the workforce and
- reduced productivity while present at work.[1]

Rules based variable
Exogenous variable
Endogenous variable
Output

1 The K10 score threshold of 15 for adjusting workforce participation days is based on the methodology outlined in the Productivity Commission's (2020) *Mental Health Inquiry*.
Source: Productivity Commission 2020 *Mental Health, Report no. 95;* Mandala analysis.

We evaluate days lost in both scenarios based on the elevated absenteeism and presenteeism for those with Kessler 10 scores >15

CGE MODELLING



- Mentally healthy workers (Kessler 10 score <15) are assumed to have 100% productivity, while those with a Kessler 10 score >15, we assume 92.08% productivity based on Productivity Commission (2020) estimates for days lost due to absenteeism and presenteeism; and the part vs full-time split.
- **B**: 4.6% represents 11 days of absenteeism out of 240 working days per year. This figure is taken from ABS National Health Survey data showing people with high K10 scores (psychological distress) take 10-12 days off work annually (11 days used as midpoint).[1]
- **C:** 6.7% represents 16 days of reduced productivity out of 240 working days. Based on ABS National Health Survey data showing people work at reduced capacity for 14-18 days annually due to psychological distress (16 days used as midpoint).[1]
- **D:** Based on reduced productivity where a 50% productivity reduction was assumed for days affected by psychological distress, as the ABS National Health Survey did not include questions about output levels on affected days.[1]
- The difference between the baseline and increased JobSeeker Payment cohort's average productivity is inputted to the Mandala G-Cubed (G20) model (v169) – a multi-country, multi-sector, intertemporal general equilibrium model. See McKibbin and Triggs (2018) for full model specifications.

Rules based variable
Exogenous variable
Endogenous variable
Output

1 Based on the methodology outlined in the Productivity Commission's (2020) *Mental Health Inquiry Report*.
Source: Productivity Commission (2020) *Mental Health, Report no. 95;* Mandala analysis.

We model the productivity effects of the enhanced number of days worked by the cohort using the G-Cubed model

G-CUBED MODELLING PARAMETERS INCLUDING SHOCK INPUTS

We used the G-Cubed (G20) model (v169) to estimate how improved mental health from higher JobSeeker payments affects workforce productivity. The model shows small but consistent gains in productivity over the 10-year period.

This approach focuses purely on quantifiable productivity gains from better mental health. The results suggests even small improvements in mental health create ongoing economic benefits through higher workforce productivity.

Category	Type	G-Cubed (G20) v169: A multi-country, multi-sector, intertemporal general equilibrium model	
G-Cubed model	REGIONS	G20 economies, rest of OECD, rest of Asia, other oil producing countries, rest of world	
	SECTORS	Sectors: Energy, mining, agriculture, durable manufacturing, non-durable manufacturing and services	
Household parameters	BEHAVIOUR	Split: forward-looking and backward-looking	Maximise intertemporal utility
	DECISION VARIABLES	Labour, consumption, investment	Subject to budget constraints
	EXPECTATIONS FORMATION	Mix of forward-looking and rule-based	
Firm parameters	PRODUCTION FUNCTION	Nested CES	
	CAPITAL TECHNOLOGY		Costly to move installed capital between sectors
	LABOUR DEMAND	Up to marginal product = real wage	
Monetary policy	INTEREST RATE SETTING	Henderson-McKibbin-Taylor rules	Central banks set short-term rates
	POLICY TARGETS	Inflation, unemployment, exchange rates (Australia: inflation targeting)	Country-specific
	RISK PREMIUM (RISR)	Exogenous term premium	Can be adjusted in simulations
Labour market	WAGE ADJUSTMENT	Sticky nominal wages	Country-specific labour contracts
	UNEMPLOYMENT	Can arise from structural or demand shocks	Short-run possibility
Productivity shock parameters	MENTAL HEALTH THRESHOLD	K10 score > 15	From Productivity Commission
	ABSENTEEISM IMPACT	4.6% (11 days/year)	ABS National Health Survey
	PRESENTEEISM IMPACT	6.7% (16 days/year)	ABS National Health Survey
	PRODUCTIVITY REDUCTION	50% during presenteeism	Model assumption
	AVERAGE PRODUCTIVITY GAIN	0.0000025% annually	Calculated impact
Implementation	SHOCK CHANNEL	Labour efficiency	Applied through productivity
	TIME PERIOD	10 years (2024-2033)	Forward projections
	GEOGRAPHIC FOCUS	Australia	Regional specification
	PARTICIPATION EFFECTS	Excluded	Isolates productivity impact
	MODEL SOLUTION	Expectations-consistent	Forward-looking equilibrium
	ADJUSTMENT SPEED	Gradual	Due to various rigidities
Stock-flow parameters	BUDGET CONSTRAINTS	Intertemporal	For all agents
	ASSET PRICES	Endogenous adjustment	Interest rates, exchange rates
	PHYSICAL CAPITAL	Sector-specific stocks	Limited mobility
	FINANCIAL FLOWS	Complete accounting	Including debt accumulation

Source: Productivity Commission 2020 *Mental Health, Report no. 95;* McKibbin and Triggs (2018); Mandala analysis.

We draw on Taylor Fry's (2021) publication of JobSeekers' justice service use rates and Dustman et al.'s elasticity estimates of welfare and crime to estimate benefits

AVOIDED JUSTICE QUANTIFICATION ASSUMPTIONS

To calculate avoided justice interactions: We use the elasticity of benefit levels to all crime reported by Dustmann et al. (2024) - a 1 percent increase in benefit levels lowers crime by an elasticity of 0.883 (year 1–5 average). In calculating benefits, we adjust for our cohort size over time for actuarial life tables and discount costs to net present values.

	RATE OF JOBSEEKER JUSTICE INTERACTIONS PER PERSON PER YEAR[1]	TOTAL YEARLY INTERACTIONS FOR 20,000 PERSON COHORT	NUMBER OF EVENTS AVOIDED PER YEAR FOR 20,000 COHORT	COST AND TYPE	NOTES
POLICE RECORDED VICTIM EVENT	0.1126	2253	*Not calculated.*		Not calculated. For victim events, we focus on avoided domestic violence (DV) as the simulation shows families experience lower financial stress. For general victim events there are complexities around recidivism as a confounding variable that may not have been fully accounted for in Dustmann et al.'s paper.
POLICE RECORDED VICTIM EVENT - DV	0.0102	204	58	$370.51	Inflated from $320 per event based on Taylor Fry's (2021) estimate.
LEGAL AID	0.0652	1305	373	$1,745.44	Inflated mid-point of the cost per event by service type range estimated by Taylor Fry (2021) of $173-$2,842.
COURTS DATA	0.07323	1465	*Not calculated.*		Not calculated. Calculations based on court finalisations (see below).
POLICE CAUTION	0.00149	30	9	$452.71	Cost inflated from $391 per event based on Allard et al. (2014) per Taylor Fry (2021).
COURT APPEARANCE	0.0721	1442	288 (finalisations)	$5,385.10 per finalisation	We divided court appearances by 5 for a conservative estimate of the number of court appearances per finalisation. Costs for magistrate's/local court inflated from Taylor Fry (2021).
CUSTODY ENDING	0.02993	599	*Not calculated.*		Not calculated due to the complexities of recidivism as a confounding variable for custody that may not have been fully accounted for in Dustmann et al.'s paper.

Sources: 1 Taylor Fry (2021) *Pathways to Homelessness.* See Table D.1. Cross table of overlaps in service use within a year. Number per 100,000 people in the NSW population per year. Average over three years to 2016/17. Dustmann et al. (2024). Refugee Benefit Cuts. *American Economic Journal: Economic Policy*, 16(2), 406–441. https://doi.org/10.1257/pol.20220062. Mandala analysis.

We estimate benefits of reducing teen delinquency drawing on Dustman et al.'s (2024) elasticities and willingness-to-pay estimates to avoid crime

AVOIDED YOUTH JUSTICE QUANTIFICATION ASSUMPTIONS

To calculate the avoided cost of youth justice: We use the costs per family of teen delinquency (estimated in willingness-to-pay terms) associated with a 40% cut in benefit levels for refugee families granted residency between 2002 and 2012, reported in Dustmann et al. (2024) scaled significantly down to our assumed rate of teen delinquency (2%) for families with team children in this sample (1,464).

Sample: From our 20,000-person representative cohort, 1,464 JobSeeker recipients have a youngest child aged between 10 and 17 years old. We assume that these children may have a teen delinquency rate of 2%, based on what we know for adults (in the absence of available data): Taylor Fry (2021)'s analysis of administrative data finds 2% of those who spent time on any form of welfare had a court appearance in the same year (See Table 15).[2] Given the teen delinquency rate in Dustmann et al.'s sample is significantly higher (28%); we scale their estimates of costs of teen delinquency per family down to our estimate of the rate in this sample (2%).

Costs are calculated in willingness-to-pay terms (estimated by Cohen & Piquero (2009)) which count the societal impact of different crimes including intangible costs like fear and community deterioration. We derive cost estimates in USD from Dustmann et al. (2024) Figure 5 which notes youth crime is a major driver of costs in years 3-8; and scale these to our sample. We convert cost estimates to AUD for the 1,464 JobSeeker recipients with a youngest child aged 10-17, and discount benefits to net present values.

YEAR	COST PER FAMILY (WITH TEEN CHILDREN) OF TEEN DELINQUENCY ASSOCIATED WITH A 40% LOWER BENEFIT LEVEL
1-2	Nil
3	$443
4	$332
5	$221
6	$277
7	$332
8	$55
9-10	Nil

Other studies also find that welfare reductions increase adolescent delinquency and risky behaviours:

- Dave et al. (2021) find no favourable behavioural effects of welfare reductions on youth; instead identifying considerable evidence of unfavourable effects for boys. Their findings suggest welfare reduction increases maternal stress/anxiety, conflict between parents and children, or parental disengagement.
- Deshpande and Mueller-Smith (2022) use a regression discontinuity design to estimate the effect of losing benefits at age 18 on criminal justice and employment outcomes over the next two decades. We find that benefit removal increases the number of criminal charges by a statistically significant 20% over the next two decades.

Sources: 1 Dustmann et al. (2024) Unintended consequences of welfare cuts on children and adolescents. *American Economic Journal: Applied Economics*, 16(4), 161–185. https://doi.org/10.2139/ssrn.4939156. 2 Taylor Fry (2021) *Pathways to Homelessness.* See Table 15. 3. Dave et al. (2021). Intergenerational Effects of Welfare Reform: Adolescent Delinquent and Risky Behaviors. *NBER Working Paper.* 4. Deshpande & Mueller-Smith (2022). Does Welfare Prevent Crime? The Criminal Justice Outcomes of Youth Removed From SSI. *NBER Working Paper.* Mandala analysis.

We draw on the Productivity Commission's (2020) costs of mental ill-health to quantify the benefits of reducing psychological distress

PER YEAR COSTS OF MENTAL ILL-HEALTH ASSUMPTIONS

2023 COST ESTIMATE BY KESSLER 10 SCORE			ASSUMPTION
COST OF MENTAL HEALTHCARE AND RELATED SERVICES	If someone's score on K10 is >22 (high or very high)	$5,993.91 per year	There are no estimates of the cost of mental-health distributed by mental health severity (e.g. Kessler 10 score) available for Australia. The best available evidence of mental healthcare and related service costs are compiled in the Productivity Commission's (2020) *Mental Health Inquiry,* which we inflate from 2019 to 2023. We construct an estimate of the mental-health cost by observing different levels of mental health usage. To get a per person estimate of the cost of mental health care for those with moderate K10 scores, we divide the PC's total cost estimate by the number of Australians who see a GP for assistance with mental health in a year (5 million). This likely gives us a slight over-estimate, as those who access a GP for mental health may not have the same level as costs as those with more severe K10 scores. For those with high or very high K10 scores, we proxy cost through dividing total costs by those who are prescribed medication for mental health by their GP (3 million). We expect this to be a significant underestimate of the costs for this group. Two thirds of government outlay for mental health is for public hospital and community healthcare, concentrated on acute care services for people with relatively more severe functional impairment as a result of mental illness. The number of Australians who receive counselling in a year is half of those prescribed medication (1.5 million). However, because we know that JobSeekers access psychologists at lower rates than the general population (see our analysis of PLIDA data in Appendix A), we have proceeded using this estimate.
	If someone's score on K10 is 16<21 (moderate)	$3,596.34 per year	
	If someone's score is under <16 (low)	$0 per year	

COST DISTRIBUTION			SOURCE
DISTRIBUTION OF COSTS OF MENTAL HEALTH CARE BY CHANNEL	Government healthcare & related expenditure (includes prevention)	63.0%	Based on Productivity Commission (2020) *Mental Health Inquiry; **Table 1.***
	Related services and supports	26.6%	
	Individual out-of-pocket expenses	4.5%	
	Insurer payments for healthcare	5.8%	
MULTIPLIER FOR INFORMAL CARE	Informal care provided by friends and family	98.7%	Cost of Informal Care Provided by Family and Friends ($15.3 billion per year) / Mental Healthcare and Related Services ($15.5 billion per year)

Sources: Productivity Commission (2020) *Mental Health Inquiry*; Mandala estimates.

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This document is intended for general informational purposes only. The analysis in this report was commissioned by the Economic Inclusion Advisory Committee within the Commonwealth Department of Social Services and prepared by Mandala.

Mandala is an economics research and advisory firm. Mandala specialises in combining cutting-edge data and advanced analytical techniques to generate new insights and fresh perspectives on the challenges facing businesses and governments.

The analysis produced in this document is current as of the date below and may be subject to change.

Note: All dollar figures are Australian dollars unless indicated otherwise.