
F Benefits of improved mental health

This appendix outlines how the possible economic and health-related quality of life benefits from improved mental health are estimated. Broadly, the estimation process involves two steps.

- Estimating the statistical relationship between mental health and wages, labour market outcomes, and health-related quality of life (section F.1) using detailed longitudinal data that is broadly representative of the Australian population (section F.2). The estimation procedure is outlined in section F.3.
- Combining this information about people’s mental health and their wages, employment and health-related quality of life with existing research that describe the possible effect of policy changes on the mental health of the target populations. The proposed reforms and estimates of the possible benefits of these reforms are presented in section F.4.

Overall, when the effects of the reforms modelled are fully realised, this might result in \$8.8 to \$11.5 billion in additional income per year, an additional 112 000 - 145 000 workers in employment, and a further 69 000 - 89 000 quality-adjusted life years (QALYs).

F.1 Mental health, labour market outcomes and health-related quality of life

Mental health is an important aspect of an individual’s ‘human capital’ — the individual attributes that affect people’s productivity, and the wages they may expect to earn if they were employed. For people already employed, improvements in mental health are likely to result in an increase in their expected wage. For people who are unemployed or not in the labour force, improved mental health is likely to increase their probability of employment, as well as their expected wage if they were to be employed. Labour demand is assumed to be perfectly elastic — that is, it perfectly accommodates changes in the labour supply.

Individuals are also likely to experience an improvement in their health-related quality of life as their mental health improves. The Commission has also estimated how improvements in mental health are likely to result in increased quality of life across the population, measured in QALYs.

Estimating the effect of mental health on employment and wages

Mental health is associated with labour market outcomes such as employment and wages (Forbes, Barker and Turner 2010). People with mental ill-health are less likely to be employed, and if they are employed they are likely to earn less (figure F.1). For example, depression can lead to absenteeism and reduced productivity (Waghorn and Lloyd 2005), and prolonged absenteeism can lead to a complete withdrawal from the labour market. It is also possible that employers can be biased and are less likely to hire someone with poor mental health.

Frijters et al. (2014) provide examples of studies that have attempted to establish causal relationships between mental health and employment (Alexandre and French 2001; Chatterji et al. 2007; Ettner, Frank and Kessler 1997). These studies find that diagnoses of psychiatric disorders and depression can reduce the probability of employment by 13–26% across different cohorts.

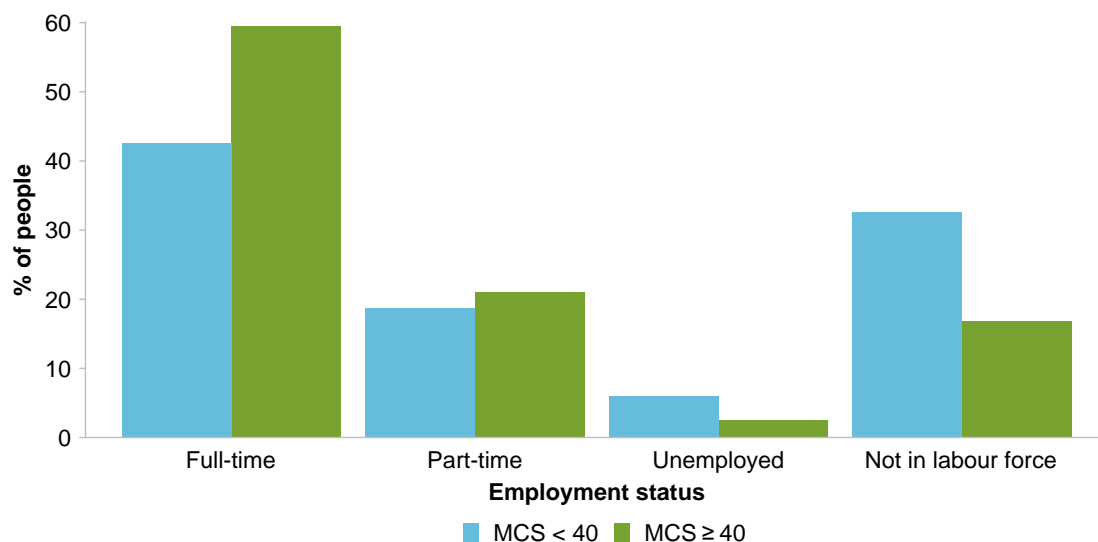
In addition to mental health, there are a range of other human capital and sociodemographic factors that are likely to affect an individual's labour force status and the wages they can expect. These include age, gender, education, marital status, work history, language and cultural background, geographical location and family composition (Cai 2010; Forbes, Barker and Turner 2010; Frijters, Johnston and Shields 2014).

Reverse causality is a problem

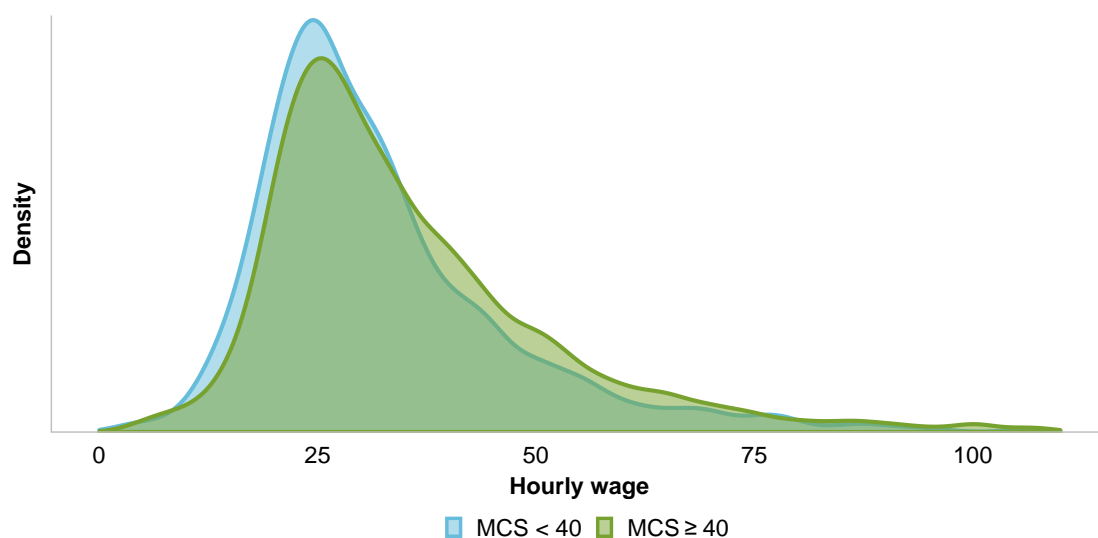
While the correlation between mental health and labour market outcomes is clear, it can be difficult to demonstrate the *causal* effects of mental health on labour market outcomes — mental health not only influences people's ability to work, but their experiences at work can also influence their mental health. This is known as a 'reverse causality' or 'endogeneity' problem.

The model used in this analysis draws on the work by Frijters et al. (2014), who studied the effects of mental health on employment using an instrumental variable model (box F.1). They address the problem of reverse causality between employment and mental health by using '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.

Figure F.1 **People with poor mental health are more likely to be unemployed or not in the labour force ...**



... and if they are employed they are likely to earn lower wages^{a,b}



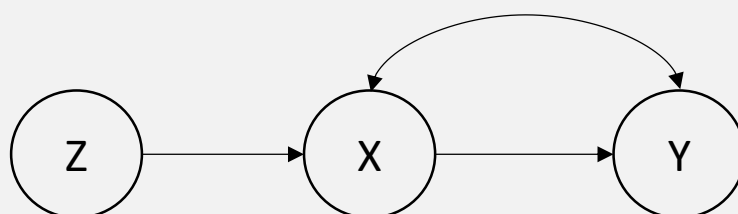
^a A mental component summary (MCS) score below 40 can be considered indicative of a mental illness (Kiely and Butterworth 2015). ^b The hourly wage is calculated as current weekly gross wage across all jobs divided by hours per week usually worked across all jobs.

Source: Housing Income and Labour Dynamics in Australia, wave 17.

Box F.1 What is an instrumental variable?

Suppose we have a dependent variable Y and an independent variable X , where there is likely to be two-way correlation or reverse causality. It is not possible to establish the size of the effect of X on Y using standard regression approaches. Instrumental variables are an econometric method that can be used to resolve problems of reverse causality.

An instrument, Z , is a variable which is correlated with X , *and* correlated with Y — but only through its effect on X . In other words, the instrument should change X and only change Y *through* its effect on X , allowing for the identification of a causal effect.



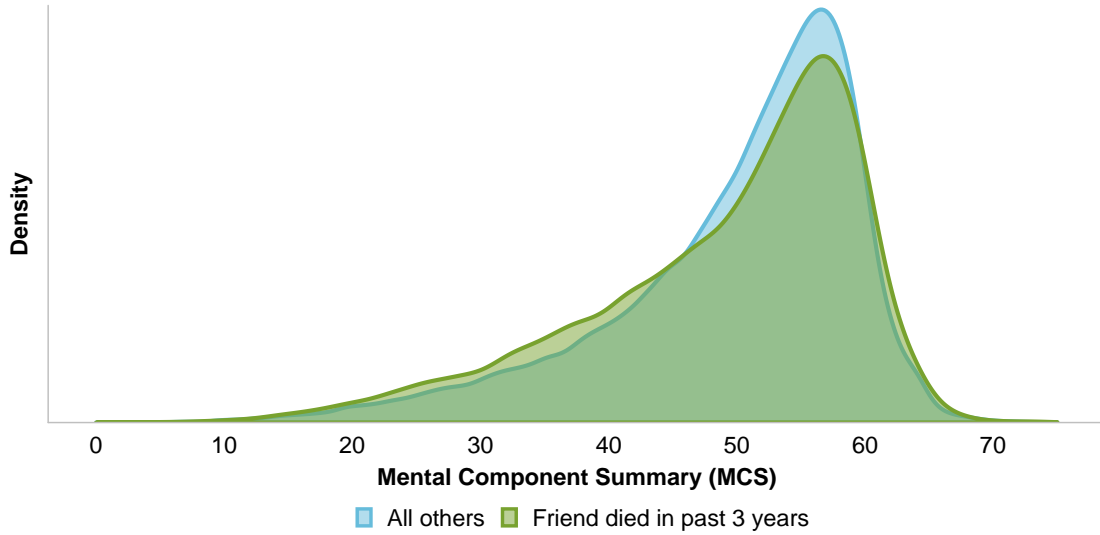
For example, suppose that we are interested in the effect of hours of attendance at a tutoring program (X) on grades (Y). The relationship between these two are likely to exhibit reverse causality — more hours at the tutoring program is likely to lead to higher grades, and students with lower grades may attend for more hours. A potential instrument for the tutoring program could be proximity to the tutoring program (Z), which can be argued to affect the hours of attendance (X) directly, and to only affect grades (Y) through its effect on hours of attendance (X).

The choice of the instrument, Z , is crucial as it is up to the researcher to argue that the instrument affects X , but is only correlated with Y through its effect on X .

This ‘death of a close friend’ instrument is found to be correlated with mental health, but independent of labour market outcomes. A literature review conducted by Frijters et al. (2014) finds that stressful life events can have substantial impacts on mental health and can increase symptoms of depression. Data from the Housing, Income and Labour Dynamics in Australia (HILDA) survey supports these findings — people who have experienced the death of a close friend in the past 3 years are more likely to be in the left-tail of the distribution of mental health scores (figure F.2).

Frijters et al. (2014) also argued that the use of ‘death of a close friend’ as an instrument is more appropriate than using the ‘death of a relative’ or the ‘death of a spouse or child’. The authors suggest that it is conceivable that a person will take time off work to look after a terminally-ill parent or their spouse/child after these events, whereas it is less likely in the case of a terminally-ill friend.

Figure F.2 **The ‘death of a close friend’ instrument is correlated with poorer mental health**



Source: Housing, Income and Labour Dynamics in Australia, waves 2–17.

The first stage equation is a linear regression:

$$MH = \alpha_1 + X_1\gamma + \delta \times \text{Death of friend} + \varepsilon_1 \quad [1]$$

where MH represents a measure of mental health, α_1 is the parameter for the intercept, X_1 is a matrix of independent variables, γ is a vector of parameters, Death of friend is the instrument, δ is the parameter associated with the instrument, and ε_1 is a vector of independently and identically normally distributed random variables with variance σ_1^2 .

The results of the first stage equation are used in several ways. The residuals are used in the second stage regression (multinomial logistic regression for employment outcomes) as part of a control function approach, and the fitted values are used in the third stage wage regression (linear regression) and the QALY regression (linear regression) as part of a two-stage least squares approach.

Mental health and employment

The second stage equation is a multinomial logistic regression, which controls for the endogenous variable (mental health) by including the residuals from the first stage as an explanatory variable. L is a categorical variable for labour force status, where the model assumes that people can either be employed full-time, employed part-time, unemployed, or not in the labour force.

$$L = \text{Multinomial Logistic}(\alpha_2 + X_2\beta + \tau \times MH + \phi\hat{\varepsilon}_1) \quad [2]$$

where α_2 is the parameter for the intercept, X_2 is a matrix of independent variables, β is a vector of parameters, τ is the parameter associated with MH, $\hat{\varepsilon}_1 = \text{MH} - \widehat{\text{MH}}$ is the residuals from the first stage equation, and ϕ is the parameter associated with the first stage residual. Because there are four categories, there are three sets of coefficients estimated.

The predicted probability of each labour force status can be estimated with the results of this regression. Let \hat{p} be the predicted probability of employment (summing up the predicted probability of working full-time or part-time) and \hat{q} be the probability of not being employed (summing up the predicted probability of being unemployed or not in the labour force).

Mental health and wages

The third stage of the model estimates a wage equation. Because we only observe wages for people who choose to work, this means that there is likely to be bias in the estimation procedure because those who are not employed are likely to be systematically different to those who are employed. For example, they tend to have lower levels of education, a greater incidence of chronic illness and a longer experience of unemployment. Human capital theory suggests that given their characteristics, if employed, these people would be expected to be less productive on average than people who are currently working, and earn lower wages.

One way to control for the bias is to use a control function approach (the Heckman correction is a prominent example of this). A third order polynomial is constructed from the predicted probability of not being employed (\hat{q}) from the second stage equation, taking into account the possibility of full-time and part-time employment. The polynomial is then included as additional predictors in the wage equation, alongside the fitted value of the measure of mental health from the first stage equation which controls for the endogeneity between wages and mental health.

$$\log(\text{Wage}) = \alpha_3 + X_3\theta + f(\hat{q})\theta_{CF} + \xi \times \widehat{\text{MH}} + \varepsilon_3 \quad [3]$$

where α_3 is the parameter for the intercept, X_3 is a matrix of independent variables, θ is a vector of parameters, $f(\hat{q})$ is a third order polynomial constructed from the fitted probability of not being employed from the second stage, θ_{CF} is a vector of parameter associated with the probabilities of not being employed, ξ is the parameter associated with the fitted value of the measure of mental health, and ε_3 is a vector of independently and identically normally distributed random variables with variance σ_3^2 . The variable used for the exclusion restriction is unemployment history (the proportion of time spent unemployed since leaving full-time education) — that is, it is included in X_2 but not X_3 .

Mental health and quality-adjusted life years

The fourth stage of the model estimates the relationship between QALYs and mental health. Using the fitted values of the measure of mental health from the first stage equation, QALYs are regressed on mental health and other characteristics.

$$QALY = \alpha_4 + X_4\zeta + \kappa \times \widehat{MH} + \varepsilon_4 \quad [4]$$

where α_4 is the parameter for the intercept, X_4 is a matrix of independent variables, ζ is a vector of parameters, κ is the parameter associated with the fitted value of the measure of mental health, and ε_4 is a vector of independently and identically normally distributed random variables with variance σ_4^2 .

Bayesian methods

Traditional, or frequentist, approaches to statistical inference typically calculate single ‘point’ estimates for each population parameter and the corresponding confidence intervals. Frequentist approaches assume that there are a ‘true’ set of underlying population parameters, and then construct an estimator, with errors resulting from finite sampling. Conclusions driven by a frequentist interpretation usually have a true/false conclusion resulting from statistical methods for testing hypotheses (Wagenmakers et al. 2008). As such, the probability assertions made under a frequentist approach are pre-sample. For example, a 95% confidence interval contains the true parameter value with probability 0.95 only before observing the data — after observing the data, the probability is either zero or one. However, confidence intervals are often incorrectly interpreted by many as a guide to post-sample uncertainty (Hoekstra et al. 2014).

Bayesian inference treats everything as random before it is observed, and everything observed as no longer random. Unobserved parameters can be therefore be constructed as probabilistic statements that are conditional on observed data. This is one of the distinguishing features of a Bayesian approach. Bayesian inference attempts to assign probabilities to different sets of parameters, given a higher weight if they are more likely to lead to the observed data (McElreath 2019). Prior probability distributions are first specified and are then updated with information arising from the data, given the assumed model structure. The resultant probability distribution (the posterior probability distribution) can be interpreted as the distribution of possible values that a parameter can take.

For this analysis, there is not likely to exist a single ‘true’ value quantifying the benefits of our reforms. Hence, Bayesian inference is used to evaluate the outcomes for many different scenarios and to assign probabilities to the likelihood of occurrence. The end product is a distribution of potential benefits and their associated credibility intervals (for example, ‘for reform X, there is a Y% chance that the labour force benefits will exceed \$Z million’).

To allow the analysis to be informed by the data, diffuse priors are used for the parameters in the model — that is, prior distributions with a relatively large variance. The priors for the regression coefficients are distributed Normal(0,10) and the priors for the standard deviations are distributed Inverse Gamma(0.5, 5).

How should parameter estimates be interpreted?

The posterior distributions from a Bayesian-estimated model are often simplified for presentation using summary statistics. The uncertainty associated with parameter values is often reported using the 5th and 95th percentiles of the posterior distribution — sometimes as a shaded area, sometimes as lines that indicate ranges. This can be interpreted as saying ‘there is a 90% chance that the true parameter value lies in this range’.

F.2 Housing, Income and Labour Dynamics in Australia

The HILDA survey is a nationally representative household panel survey, conducted annually, containing respondents’ information regarding a range of different areas including education, health, labour force status, and demographics. As of October 2019, there were seventeen waves of data available which are used in our analysis.

Following Frijters et. al. (2014), the analysis is focused on the Australian population aged between 21–64 years. Summary statistics for individual level characteristics are presented in table F.1. Mental health is measured using the mental component summary (box F.2).

Table F.1 Sample means of key variables^{a,b}

	<i>All respondents</i>	<i>MCS ≤ 40</i>	<i>MCS > 40</i>
Employed	0.752	0.587	0.783
Full-time employment	0.551	0.407	0.578
Part-time employment	0.201	0.180	0.205
Unemployed	0.030	0.054	0.026
Not in the labour force	0.218	0.360	0.191
Unemployment history	0.041	0.066	0.037
Mental component summary (MCS)	49.773	31.580	53.222
Physical component summary (PCS)	51.063	49.422	51.374
Quality-adjusted life years	0.666	0.365	0.723
Female	0.524	0.585	0.512
Age	41.939	41.340	42.053
Highest qualification – University degree	0.296	0.242	0.306
Highest qualification – Diploma/certificate	0.322	0.318	0.323
Highest qualification – Year 12	0.153	0.160	0.151
Married	0.695	0.570	0.719
Lives in regional area	0.306	0.311	0.305
Aboriginal or Torres Strait Islander	0.019	0.029	0.017
Non-English speaking background	0.172	0.165	0.174
Currently studying	0.041	0.047	0.040
Number of children between ages 0–4 years	0.209	0.183	0.213
Number of children between ages 5–14 years	0.386	0.374	0.389
Number of children between ages 15–24 years	0.304	0.294	0.306
Windfall income (\$000s)	0.226	0.221	0.227
Many friends	4.413	3.638	4.560
Death of a spouse in the past 3 years	0.012	0.023	0.010
Death of a relative in the past 3 years	0.248	0.279	0.242
Death of a friend in the past 3 years	0.178	0.214	0.171
Sample size	131 303	21 053	110 250

^a A mental component summary (MCS) score below 40 is considered indicative of mental illness (Kiely and Butterworth 2015). ^b Waves 2 to 17 of HILDA are pooled for estimation.

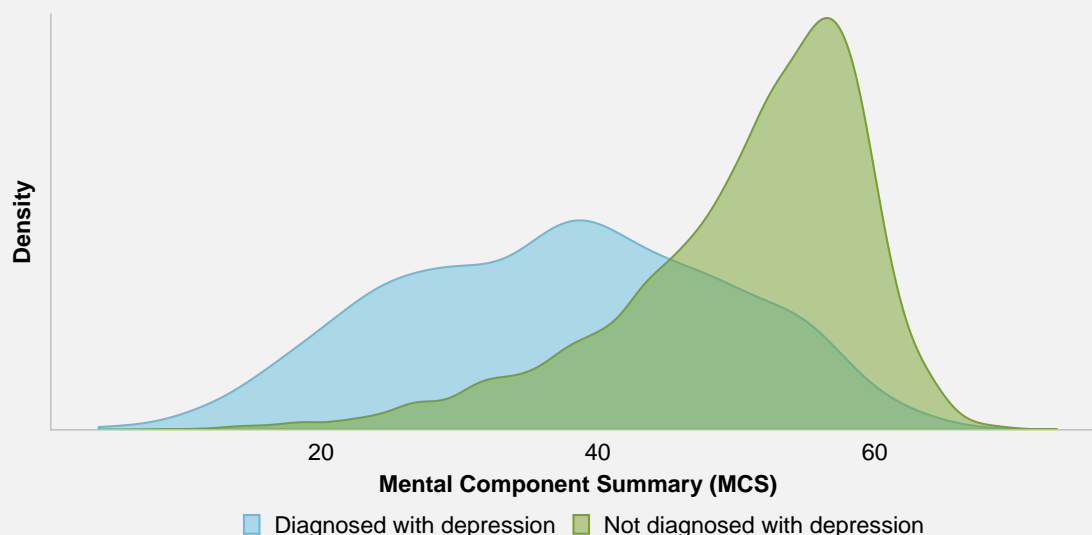
Source: Housing, Income and Labour Dynamics in Australia, waves 2–17.

Box F.2 **Measuring mental health using the mental component summary**

The measure of mental health used for this analysis is called the mental component summary (MCS). The MCS is derived from responses to the Short Form 36 (SF-36) questionnaire, and transformed into a range from 0 to 100, with a mean of 50 and standard deviation of 10, with higher scores corresponding to better mental health (Ware and Kosinski 2001).

While the SF-36 does not include references to symptoms of specific diseases, the measures derived from it have been shown to be highly correlated with the frequency and severity of many health problems. The SF-36 is comprised of 36 questions relating to different aspects of an individual's health-related quality of life. The 36 questions are used to derive eight subscales of health, each ranging from 0 to 100, and measuring different elements of health: physical functioning; limitations in carrying out usual role due to physical problems; bodily pain; perception of general health; vitality; social functioning; limitations in carrying out usual role due to emotional problems; and mental health. The physical and mental health summary measures are produced by aggregating the most correlated of the subscales.

To check the validity of the MCS as a measure of mental health, we compare the distribution of the MCS between those who have been diagnosed with long-term depression before (where long-term is defined as lasting or expected to last for at least six months), and those who have not been diagnosed with depression. The figure below suggests that the MCS is correlated with the diagnosis of depression, where people with lower MCS scores are much more likely to have been diagnosed with depression. Additionally, the question refers to a lifetime diagnosis of long-term depression and so will also include people in recovery.



Sources: Ware and Kosinski (2001); Housing, Income and Labour Dynamics in Australia, wave 17.

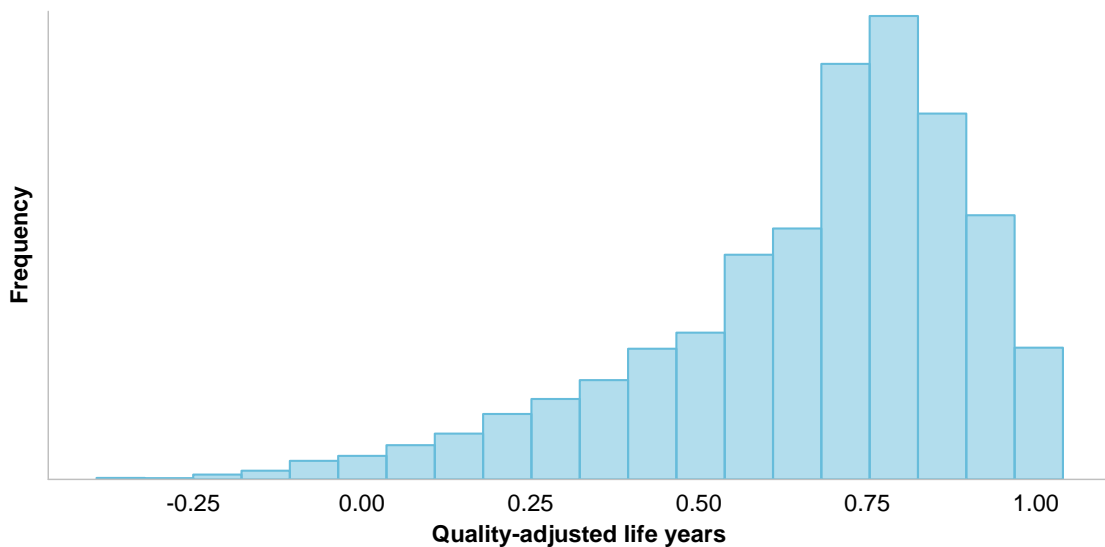
Health-related quality of life

Health-related quality of life is measured in terms of QALYs. A QALY is the arithmetic product of life expectancy combined with a measure of the quality of life-years remaining.

The time a person is likely to spend in a particular state of health is weighted by a ‘utility’ score from standard valuations. 1 equates to perfect health and 0 equates to death. Certain health states can be assigned a negative value as they may be characterised by severe disability and/or pain that are regarded as worse than death (Whitehead and Ali 2010). In HILDA, the distribution of QALYs is left-skewed, with the majority of people having between 0.6–0.8 QALYs. (figure F.3).

If an intervention provided perfect health for one additional year, it would produce one QALY. Likewise, an intervention providing an extra two years of life at a health status of 0.5 would equal one QALY.

Figure F.3 Distribution of quality-adjusted life years in HILDA



Source: Housing, Income and Labour Dynamics in Australia, waves 2–17.

F.3 Estimating parameters

Before estimating the model, continuous variables are rescaled so that the posterior distributions can be estimated more efficiently. In most cases, this involves normalising the variables to zero mean and unit standard deviation. Some variables are categorical variables that need to be interpreted relative to a baseline (table F.2).

Table F.2 Categorical variables — baseline

<i>Variable</i>	<i>Relative to ...</i>
Multiple categories	
Age 21–24 years, Age 25–44 years	Age 45–64 years
Vic, Qld, SA, WA, Tas, NT, ACT	NSW
University degree, Diploma/certificate, High school	Did not graduate high school
Binary categories	
Female	
Married/de facto	
Lives in a regional area	
Aboriginal and Torres Strait islander	
Non-English speaking background (NESB)	
Currently studying	
Death of a friend/spouse/relative in the past 3 years	

How were our results estimated?

The Commission used the statistical package Stan (Carpenter et al. 2017) through an interface to the R programming language.

For all but the simplest cases there is no mathematical equation that defines the posterior distribution — it needs to be estimated empirically. This estimation can be computationally difficult, indeed it has only been possible to estimate complicated models in recent years, as computing power has increased. Stan uses an algorithm called Hamiltonian Monte Carlo to explore and sample from the posterior probability distribution. Statistical inference about the posterior distribution is conducted using these samples.

F.4 Reforms that will improve mental health

Calculating the expected effects of policy changes

The direct economic benefits of improvements in mental health may be thought of as consisting of two elements — increases in expected income and increased employment.

The reforms are modelled as functions that transform the relevant pre-reform variables into post-reform variables. This will primarily be the mental health variable.

$$MCS_i^{\text{post}} = f_j(MCS_i^{\text{pre}}) \quad [5]$$

where f_j is a function indicating how the mental health of individual i changes as a result of reform j . This function is informed by past research and a range of necessary assumptions detailed below in table F.3.

The additional number of workers is the change in the expected aggregate labour supply (which includes both full time and part time employment) between pre- and post-reform:

$$\Delta \text{Employed} = \sum_i \hat{p}_i(\text{MCS}_i^{\text{post}}) - \sum_i \hat{p}_i(\text{MCS}_i^{\text{pre}}) \quad [6]$$

The labour market benefits are calculated as the change in expected aggregate income between pre- and post-reform. In this model, the change in aggregate income can come from either a change in wages attributed to changes in mental health or a change in the probability of working full-time or part-time (and the associated average number of hours worked).

$$\Delta \text{Income} = \text{Weeks} \times \text{Hours}^{\text{FT}} \times \quad [7]$$

$$[\sum_i \text{Wage}_i(\text{MCS}_i^{\text{post}}) \hat{p}_i^{\text{FT}}(\text{MCS}_i^{\text{post}}) - \sum_i \text{Wage}_i(\text{MCS}_i^{\text{pre}}) \hat{p}_i^{\text{FT}}(\text{MCS}_i^{\text{pre}})]$$

$$+ \text{Weeks} \times \text{Hours}^{\text{PT}} \times$$

$$[\sum_i \text{Wage}_i(\text{MCS}_i^{\text{post}}) \hat{p}_i^{\text{PT}}(\text{MCS}_i^{\text{post}}) - \sum_i \text{Wage}_i(\text{MCS}_i^{\text{pre}}) \hat{p}_i^{\text{PT}}(\text{MCS}_i^{\text{pre}})]$$

Similarly, the change in QALYs is

$$\Delta \text{QALY} = \sum_i \text{QALY}_i(\text{MCS}_i^{\text{post}}) - \sum_i \text{QALY}_i(\text{MCS}_i^{\text{pre}}) \quad [8]$$

Waves 2–17 of HILDA are used to estimate the parameters of the model following the procedure outlined in section F.1. In constructing the dataset used for the analysis, observations are dropped when an individual has not provided a complete set of responses to the questions used to construct the variables required for estimation. To estimate the benefits of the proposed reforms, the latest wave of HILDA is used as it is expected to more closely reflect the current state of the Australian population.

Unless otherwise specified, the results are presented for a single year, where aggregate income is calculated assuming that an individual is paid for 52 weeks per year, with an average of 43.6 hours worked per week for those employed full time, and 21.7 hours worked per week for those employed part time (using data from HILDA wave 17).

The Bayesian approach to estimating the relationships between mental health and wages, labour force participation, health-related quality of life (QALYs) produces a distribution over the parameters, rather than a single ‘point’ estimate. Using the output from the models described in section F.1 combined with a set of reforms yields a range and distribution of possible expected effects (box F.3).

Box F.3 **Interpreting outputs from Bayesian statistical models**

Bayesian methods deliver parameter estimates spanning a range of possible values. The choice of which statistic to present in summarising the outputs requires judgment.

In this work, the median (50th percentile) is preferred as it represents outcomes with a reasonable chance of occurring and is not skewed, as the mean can be, by outlier results. Uncertainty associated with an estimate is often indicated by presenting values from percentiles at the top and bottom of the span. The value at the 90th percentile, for example, can be interpreted as meaning that ‘there is only a 10% probability that the true parameter value is greater than this figure’. Values between the 5th and 95th percentiles can be interpreted as indicating that ‘there is a 90% chance that the true parameter value lies in this range’. This is sometimes referred to as a *credibility interval*.

For each reform, there is a probability distribution constructed for the estimated benefits. For example, the changes in early childhood education yield a median increase in employment of 50 700 workers. This means that there is a 50% chance that we will have up to 50 700 additional workers. Similarly, the 95th percentile suggests there is a 95% chance that there will be up to 58 500 additional workers (and a 5% chance that it will exceed this).

Table F.3 **Reforms, populations, and benefits**

			Median estimates of extra ...		
Reform	Population affected (coverage)	Effect size	Employed	Income	QALYs
Healthcare					
Expanded use of supported online treatment	People with a mild mental illness (MCS between 31 and 40) who are not currently seeing a psychologist. Initial uptake is assumed to be 50 000 people.	0.22 SD improvement in mental health (2.2 point increase in MCS) based on Andrews et al. (2018).	2365	226.9	1683
Additional community ambulatory mental health services	People with a moderate mental illness (MCS score between 25 and 31) who have seen a psychologist in the past 12 months. Assume an additional 75 000 people will be treated each year.	Average change in the K10 between admission and discharge for ambulatory services is 8.4 points (AMHOCN 2019), which is approximately a 10.1 point increase in MCS.	14 242	1313.2	11 514
Additional non-acute beds	People with a severe mental illness (MCS score between 17 and 24). This omits people with the most severe mental illness, whose needs will not be met by non-acute beds. Assume an additional 20 000 people will be treated each year.	Average change in the K10 between admission and discharge for residential treatment is 5.7 points (AMHOCN 2019), which is approximately a 6.8 point increase in the MCS. As many of the people benefiting from these services will already be receiving treatment (they have severe mental illness, and may be in acute care) it is assumed that the average effect is half this (a 2.85 point improvement in K10, or 3.4 point increase in MCS).	1472	125.5	1052
Improved social and emotional learning in early childhood and school education	Everyone who is of working age (in terms of the 2017 population, this equates to 14.6 million people). However, only 6.3 million people are expected to benefit (those with below average mental health).	0.04 SD improvement in mental health (0.4 point increase in MCS), taken from the lower bound of Sklad et al. (2012).	50 734	4938.1	37 960

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Table F.3 (continued)

Reform	Population affected (coverage)	Effect size	Median estimates of extra ...		
			Employed	Income	QALYs
Improved aftercare for those who attempted suicide	Of those who would have completed suicide, or would be incapacitated by their attempt, 1073 are prevented. A second effect is included for those who would have a short absence from work due to a suicide attempt, but are not permanently incapacitated. This covers 5108 short absences from work.	There were approximately 2500 deaths due to suicide in the working age population (ABS 2019) and there were 31 083 hospitalisations due to self-harm in 2017-18 (AIHW 2019). Aftercare can lead to a 19.8% reduction in subsequent suicide attempts and a 1.1% reduction in the suicide rate (Krysinska et al. 2016). Kinchin and Doran (2017) estimate that 17% of suicide attempts result in full incapacity, and 83% lead to a short absence from work.	829	54.3	696
Changes to workers compensation for mental health related claims	Between 11 000 and 13 000 people return to work earlier than otherwise. This includes the 7200 people who have mental health-related claims for workers compensation. Because these claims are related to mental health, it is assumed that the group have an MCS score below 40.	Time spent reliant on workers compensation is halved for people making a mental health claim.	..	121.3	..
Expanded Individual Placement Support program	An individual placement support rollout could be of the order of 50 000 people with severe mental illness (an MCS score between 17 and 24).	One-third of those who receive IPS are assumed to work part-time for five hours per week (Latimer, Xie and Lecomte 2006).	550	3.1	..
Additional Youth Individual Placement Support places	1000 people aged 21 to 25 who are not in education, employment, or training who have an MCS score below 40.	About 20% of these people are placed into education or training, and 55% are placed into employment. Of those entering employment, all are expected to work part-time for five hours per week (Latimer, Xie and Lecomte 2006).	16 667	106.4	..

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Table F.3 (continued)

Reform	Population affected (coverage)	Effect size	Median estimates of extra ...		
			Employed	Income (\$m)	QALYs
Additional psychosocial supports	About 272 000 people aged 18–64 years require psychosocial support services, but only 90 000-95 000 are currently accessing services, leaving about 180 000 who could benefit from access to psychosocial support services. People requiring access to psychosocial support are likely to be in the bottom range of the MCS distribution, with those already accessing psychosocial support services having the lowest scores. Hence the target population has an MCS score of between 18 and 21.	Muir, Meyer and Thomas (2016) conducted an evaluation of the Wellways Partners in Recovery program and estimated an effect size of 0.44 on the 'managing mental health' dimension (translating to an increase of 4.4 MCS points).	19 210	1580.8	12 042
Stigma reduction	People with a diagnosed mental illness are expected to benefit from a reduction in social stigma. People with worse mental health are expected to benefit most from reduced stigma, while those with moderate/mild forms of mental illness are less likely to be stigmatised and benefit less.	People with a MCS score less than 30 are assumed to experience a one point increase in MCS, while those with an MCS score between 30 and 35 experience a 0.5 point increase. Those with an MCS score above 35 will experience a 0.1 point increase.	19 657	1549.4	13 577
Carer benefits from improved services for consumers	Reforms can help carers assisting people in the 'missing middle'. About 42 000 people are caring for someone in the 'missing middle'.	From the Survey of Disability, Ageing and Caring (2016), it is estimated that 35% of primary mental health carers took on a caring role because alternative care was too costly, there were no other care arrangements available, or they had no other choice. By providing more formal care, it is assumed that these carers will no longer need to provide informal care, which will allow for increased opportunities for carers to enter the workplace.	2551	136.7	..

.. Not applicable

Source: Productivity Commission estimates using HILDA.

Table F.4 Estimated range of benefits of proposed reforms

	<i>5th percentile</i>	<i>Median</i>	<i>95th percentile</i>
Online supported treatment			
Additional people employed	2023	2365	2713
Additional income (\$m)	196	227	255
Additional QALYs	1482	1683	1903
Community ambulatory services			
Additional people employed	12 382	14 242	16 001
Additional income (\$m)	1138	1313	1478
Additional QALYs	10 146	11 514	13 009
Non-acute beds			
Additional people employed	1262	1472	1689
Additional income (\$m)	108	126	143
Additional QALYs	927	1052	1188
Children and young people			
Additional people employed	43 132	50 734	58 515
Additional income (\$m)	4266	4938	5569
Additional QALYs	33 445	37 960	42 912
Suicide prevention (annual)			
Additional people employed	823	829	835
Additional income (\$m)	54.7	55.3	55.9
Additional QALYs	692	696	700
Suicide prevention (lifetime)			
Additional income (\$m)	1308	1322	1337
Workers compensation			
Additional income (\$m)	118.8	121.3	123.9
Individual Placement and Support			
Additional income (\$m)	103.6	106.4	109.3
Youth Individual Placement and Support			
Additional income (\$m)	2.99	3.05	3.11
Psychosocial supports			
Additional people employed	16 686	19 210	21 879
Additional income (\$m)	1368	1581	1798
Additional QALYs	10 604	12 042	13 615
Stigma reduction			
Additional people employed	16 631	19 657	22 670
Additional income (\$m)	1340	1549	1761
Additional QALYs	11 971	13 577	15 342
Carers			
Additional people employed	2113	2551	2973
Additional income (\$m)	111	137	162

^a While there is an increase in employment from individual placement support programs, it is not shown here since it based on a static assumption and hence do not have a distribution.

Source: Productivity Commission estimates using HILDA.

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