Horizontal inequity in the use of mental healthcare in Australia

Abstract

For people experiencing mental health problems, timely access to high-quality healthcare is imperative for improving outcomes. However, limited availability of services, high out-of-pocket costs, insufficient health literacy and stigmatising attitudes may mean people do not receive the necessary treatment. We analyse Australian longitudinal data to document the extent and predictors of horizontal inequity in mental healthcare use among people with a newly developed mild or moderate mental disorder. Importantly, we compare people with similar health, residing in the same area, thus controlling for differences in healthcare needs and availability of services. Results suggest that mental healthcare use is not significantly associated with household income or financial hardship. In contrast, we find significant inequities by educational attainment, with university graduates around 50% more likely to receive mental healthcare than high-school dropouts. These findings are robust across subsamples and alternative modelling approaches, including panel data models with individual fixed-effects. Additional explorations of the education gradient suggest a potential pathway through mental health-specific knowledge and attitudes.

Keywords: Mental Health, Healthcare, Inequity, Income, Education

1. Introduction

A major challenge for healthcare systems is meeting increasing demands for mental healthcare services and reducing disparities in access. A key concern is horizontal inequity, which violates the principle that people with equal needs should be treated equally, irrespective of other (non-need) characteristics, including ability to pay (e.g. O'Donnell and Propper, 1991; Wagstaff et al., 1991; Culyer and Wagstaff, 1993). The extent of horizontal inequity is often viewed as a good indicator of healthcare system performance, and eradicating inequity is thus a principal policy objective in many countries (e.g. Morris et al., 2005; Bago d'Uva et al., 2011; Cookson et al., 2016; Pulok et al., 2020). In this paper, we characterise the extent and predictors of horizontal inequity in the Australian mental healthcare system.

Over the last thirty years, an extensive literature has tested for horizontal inequity and broader distributional concerns in the use of healthcare services, including general practitioners, in-patient and out-patient hospital care, and specialist medical services. A key focus has been to identify the extent of income-related inequities. While the magnitude of income-related inequities differs across studies and regularly by country and type of healthcare, it is often found that GP services are pro-poor, while specialist services are pro-rich (e.g. Van Doorslaer et al., 2000, 2008; Cookson et al., 2016; Fiebig et al., 2021). However, the drivers of inequity in mental healthcare use may differ from other healthcare types due to the unique nature of mental health problems. For instance, individuals are often unaware of their mental health needs or the available treatment pathways, and individuals may be reluctant to use services because of the stigmatising attitudes still prevalent across most societies (Mangalore and Knapp, 2006). Moreover, income-related inequality for psychiatric disorders is often found to be higher than for general health, especially for more severe conditions, such as psychosis (Mangalore et al., 2007).

Most evidence on socioeconomic inequities in mental healthcare use comes from studies that inadequately control for differences in healthcare needs (i.e. mental ill-health). If a person's need for treatment is not controlled for, then the association between socioeconomic status (SES) and need will confound the estimated association between SES and mental healthcare use. Given the higher prevalence of mental ill-health among individuals from lower socioeconomic backgrounds, it would most likely bias the SES estimate such that it falsely appears there are pro-poor inequities in access. There is also a particular absence of longitudinal analyses in the literature (Pulok et al., 2020).

Furthermore, results from the existing literature are mixed, with some studies finding no evidence of socioeconomic inequities (e.g. Algeria et al., 2000; Bebbington et al., 2003; Burnett-Zeigler et al., 2012; Hashmi et al., 2022) and other studies finding large disparities (e.g. Steele et al., 2006, Jokela et al., 2013; Bartram and Stewart, 2019; Lopes et al., 2023). Given the methodological limitations and mixture of results, providing additional evidence on inequities in mental healthcare is needed.

This paper provides new evidence by analysing data from the long-running Household, Income and Labour Dynamics in Australia (HILDA) survey. A unique advantage of HILDA is that it includes longitudinal information on SES (e.g. income, wealth, financial hardships and education), detailed location of residence, regular health modules (e.g. SF-36 and Kessler Psychological Distress Scale), and questions regarding mental healthcare use. These features allow us to test for socioeconomic inequities while controlling for healthcare needs, availability of services (through neighbourhood fixed-effects), and time-invariant factors, such as a person's preferences and health background (through individual fixed-effects). Additionally, we extend previous studies by exploring the potential importance of health-specific knowledge (measured by a health-related post-school qualification) and individual characteristics that are known to be correlated with SES and health-related behaviour, such as personality and social support.

Moreover, the Australian setting is an interesting context for analysing mental healthcare inequities. Around 20% of Australians experience mental illness in any given year (Australian Bureau of Statistics, 2022), but 44% with a mental illness report that they did not receive recommended care because of costs (Callander et al., 2017).

We find little evidence of horizontal inequity by ability-to-pay (i.e. low household income and financial difficulties) among people with a newly developed mild or moderate mental disorder, using both between- and within-individual variation. In contrast, we find evidence of substantial inequity by educational attainment. Conditional on need, people with a university degree are around 4.6 percentage points more likely to see a mental health professional in the next 12 months than high school dropouts. Moreover, the association between changes in poor mental health and mental healthcare use over time is 4.3 percentage points higher if the person has a university degree. These findings hold across different subsamples (age, gender, location of residence, and years) and regression specifications.

2. Mental healthcare in Australia

In 2020-21, 11% of Australians (2.9 million people) accessed 14 million publicly-funded mental health services. Around half (48%) were provided by psychologists, 19% by psychiatrists and 29% by general practitioners (Australian Institute of Health and Welfare, 2022). These service types are generally subsidised through Medicare, Australia's public healthcare payment system. More specifically, subsidies extend to almost all consultations with GPs and psychiatrists and up to ten consultations per year with psychologists (through the Better Access program). However, although Medicare subsidies make mental healthcare more affordable, providers can charge patients additional fees. A recent evaluation of psychological services funded through the Better Access program found that 47% of services and 65% of treatments involved a co-payment, with the median out-of-pocket cost equalling AUD$74 (Pirkis et al., 2022). In addition to out-of-pocket costs, Australia's mental healthcare system suffers from rationing and long waiting times due to a shortage of trained medical professionals and complex and fragmented systems (Productivity Commission Inquiry, 2020; NAPP, 2021; Victorian Royal Commission, 2021). More generally, there is concern that access to mental healthcare services is not equitable, with poverty and social disadvantage making it difficult for people to access necessary services, and that there is a 'postcode lottery' that is worse in rural and regional areas.

Several studies have tested for inequalities in mental healthcare use in Australia. A prominent study is Meadows et al. (2015), which analysed Medicare administration records on GP, psychiatrist and psychologist services from 2007 to 2011. They found that individuals living in more socioeconomically disadvantaged postcodes use fewer services, with the largest gap found for psychiatric services, which tend to have the highest out-of-pocket costs. However, this administrative data did not provide any measures of need, which limits conclusions about the extent of horizontal inequity. Bartram and Stewart (2019) compared the extent of income-based inequities in access to psychotherapy and other mental health services in Canada and Australia. For Australia, analysing cross-sectional data from the 2007 Australian National Survey of Mental Health and Well-Being, and after standardising for need and controlling for non-need demographic variables, they find no significant income-related inequities for the use of psychologists, but that the use of psychiatrists is pro-poor.

More recently, Hashmi et al. (2023) analysed data from HILDA's 2009 and 2017 waves to study inequity in mental healthcare use. They found evidence of education-related inequity in 2009, but no income-related inequity in 2009 or 2017 nor education-related inequity in 2017. Despite using the same dataset as in this study, the results in Hashmi et al. (2023) differ somewhat from those presented below. For instance, we find that the educational gradient was weakest in 2009 and strongest in 2017. Differences in results likely stem from differences in estimation samples (e.g. we focus on a subsample of people needing healthcare) and empirical approaches (e.g. we estimate panel data models).

3. Data, measures and associations

3.1. Description of the HILDA Survey sample

The Household, Income and Labour Dynamics in Australia (HILDA) Survey is an ongoing annual household-based longitudinal study that commenced with a nationally representative sample in 2001. In each wave, all household members over 15 years are asked to complete a face-to-face interview and a self-completion questionnaire. These two questionnaires cover issues such as economic status, labour market dynamics, family life, health, and wellbeing (Watson, 2021).

A key feature of HILDA for this study is that it measures mental health annually and mental healthcare use periodically (in waves 9, 13 and 17). This means we can control for healthcare needs at the time of the survey (wave t) and observe healthcare use in the subsequent 12 months (as reported in wave t+1) for three survey waves. It also implies we can estimate models that use both between-individual and within-individual variation in ability-to-pay, need and healthcare use.

An important sample restriction is the exclusion of individuals who report in waves 8, 12 or 16 that they have a serious long-term mental illness or disability that restricts them in their everyday activities and has lasted or is likely to last six months or more. This equates to the omission of 1515 observations from 1116 individuals (4.5% of the restricted sample). We impose this restriction to reduce endogeneity concerns, where a past mental illness causes lower SES and greater mental healthcare use. The omission of people with a serious mental illness means we focus mainly on inequities in mental healthcare use following new, mild and moderate common mental disorder.[1]

We also restrict the sample to those aged 21-79 in the wave when mental health (need) is measured, so that most people have completed their formal education and reside independently. Finally, we omit people with missing mental health and healthcare information.[2] Implementation of the age, mental illness, and missing information restrictions generates a sample of 16,082 individuals and 32,301 observations across three waves. This sample is further reduced in regression analyses when we condition on having poor mental health (high mental healthcare need).

3.2. Measuring health and healthcare use

Our main measure of poor mental health comes from the Short-Form Health Survey (SF-36), which is in the self-completion questionnaire each wave, and has been shown to have good psychometric properties (Ware et al., 1994). The SF-36 categorises 36 items into 8 dimensions: mental health,

[1] Including individuals with a serious long-term mental illness in the estimation sample causes the estimated socioeconomic inequities to become larger in magnitude.

[2] Estimated predictors of missingness, based on prior wave information, include respondent age, marital status, children, and physical health. Importantly, mental health is not a significant predictor.

physical functioning, physical and emotional limitations, social functioning, bodily pain, general health. The Mental Health dimension (MHI-5) is created from responses to 5 SF-36 questions that ask respondents how much time during the past 4 weeks they have felt nervous, so down in the dumps that nothing could cheer you up, calm and peaceful, down, and happy. Possible responses range from all of the time to none of the time. The MHI-5 is calculated as the sum of (some reverse coded) responses and transformed to a 1 to 100 scale. Appendix Figure A1 presents the distribution of MHI-5 scores, illustrating its negative skew, with most people reporting good mental health. In a robustness test, we additionally measure mental health using the Kessler Psychological Distress Scale (K10). The K10 is a widely used screening tool for mental illness in the general population (Kessler et al., 2003), but is not collected annually in HILDA.

In addition to controlling for mental health, we control for the possibility that people with physical health problems have higher mental healthcare needs. We do this by including the eight SF-36 dimension scores and 15 binary indicators of long-term health conditions in all regressions (e.g. hearing problems, limited use of feet or legs, shortness of breath or difficulty breathing, and chronic or recurring pain).

Mental healthcare use is established based on a question from waves 9, 13 and 17, “During the last 12 months, have you seen any of these types of healthcare providers about your health?”, to which a possible response option is, "A mental health professional, such as a psychiatrist or psychologist". The advantage of this broad self-reported measure is that it includes publicly and privately funded mental healthcare services received in a range of settings (e.g. clinics, hospitals, work, university, etc.). Measures based on Medicare administrative records, for example, only encompass publicly funded care received in particular settings. A potential limitation of the HILDA measure is that it is self-reported and therefore may contain measurement error.

The strong link between mental healthcare use and mental health, as measured by the MHI-5 score, is illustrated in Figure 1. Those with poor mental health (reported in year t) have a considerably higher likelihood of receiving mental healthcare in the next 12 months (reported in year t+1). For instance, people with very low MHI-5 scores (< 20) have healthcare use rates of around 50%, while those with high scores of (> 80) have healthcare use rates close to 0%. Nevertheless, Figure 1 demonstrates that many people who report always feeling so down in the dumps that nothing could cheer them up and never feeling happy (i.e. a low MHI-5 score) do not visit a mental health professional.

3.3 Measuring socioeconomic status

We focus on three measures of SES. First, we use equivalised total annual household income to capture a person's ability to pay out-of-pocket healthcare costs. Income measurement is a key feature of the HILDA survey, with income information collected from all adult household members through a lengthy questionnaire module. Second, we use a binary variable indicating that the person is experiencing financial difficulty. Specifically, individuals are asked whether, due to a shortage of money, they "Could not pay electricity, gas or telephone bills on time". This measure supplements the household income variable by capturing a person's inability to pay out-of-pocket healthcare costs even though they may have a high annual income; for example, because they have many essential expenditures.

Our third measure of SES is highest educational attainment. An extensive economics literature has established strong links between education and health outcomes, and there are a number of potential pathways linking education to healthcare use, conditional on need (Cutler and Lleras-Muney, 2010). Education may be particularly important for mental healthcare use given the established issues regarding high stigma and poor mental health literacy.

Notably, these socioeconomic variables are measured at time *t*, before the measurement of healthcare use at time *t*+1. In robustness analyses, we vary the timing such that SES is measured several years earlier. The motivation is to limit the likelihood that the occurrence of poor mental health or the receipt of mental healthcare is causing changes in our measures of SES.

Figure 2 illustrates the associations between SES and mental healthcare use for the sample with low mental health (high need), defined as a MHI-5 score of less than 68. This cut-off score is from Kelly et al. (2008), which uses data from the British Household Panel Survey (BHPS) to compare MHI-5 scores with scores from the General Health Questionnaire (GHQ-12), which has validated cut-offs. Graph A demonstrates that for each household income quintile, less than 13% of individuals saw a mental health professional. There is evidence of a modest income gradient, with those in the highest income quintile having a roughly 2 percentage point higher rate than those in the second lowest quintile. In contrast, Graph B demonstrates a strong education gradient: 7.8% of high school dropouts received mental healthcare, compared with 14.5% of university graduates. These bivariate correlations suggest that educational attainment is a more important predictor of future mental healthcare use than household income.

Finally, Table 1 presents sample means for SES, key individual characteristics (sex, age, marital status, children), and health, separately for the full sample (defined in Section 3.1) and for a sample with poor mental health (MHI-5 < 68). It is clear that the sample with poor mental health have lower SES and are in worse health (both physically and mentally). This sample also contains a higher proportion of women, younger people, and people who are not married or cohabitating (relative to the full sample).

4. Between-individual, within-area analysis

We begin by presenting estimated associations between SES (measured in waves 8, 12 and 16) and mental healthcare use (measured in waves 9, 13 and 17), using the sample of respondents with poor mental health (MHI-5 < 68). This regression approach can be represented by equation (1):

$$mhcare_{i,t} = \alpha_0 + \alpha_1' SES_{it} + \alpha_2' H_{it} + \alpha_3' X_{it} + \alpha_4' AREA_{it} + \lambda_t + \varepsilon_{i,t} \quad (1)$$

The approach controls for mental healthcare need through the aforementioned sample restrictions and by including the eight SF-36 subscales (including mental and physical dimensions) and 15 indicators of long-term health conditions (H_{it}). The regression also includes area fixed-effects ($AREA_{it}$), based on Statistical Area Level 3 (SA3) geographical areas, and covariates representing demographic characteristics (X_{it}): age, gender, marital status, number of children, country of birth, and non-English language spoken at home. The inclusion of area fixed-effects implies that the coefficients of primary interest (α_1) are identified from within-area variation in individual SES. We apply this approach, which differs from most other studies, because in this paper our aim is to focus on the demand-side determinants of horizontal inequity by comparing people with the same potential healthcare supply (i.e. availability of mental health services).

An important issue that we cannot empirically address is the heterogenous reporting of health. If a person's perception of their health and their willingness to report poor health vary with SES, then self-reported health will not provide a good control for healthcare needs, potentially biasing estimates of the determinants of horizontal equity (Bago d'Uva et al., 2011). For example, van Doorslaer et al (2004) show that evidence of pro-poor GP service use may be (partly) driven by the tendency for lower SES groups to under-report poor health. If there is similar heterogeneous reporting of mental health in our data, then it may cause a downward bias in the income and educational attainment estimates.

4.1. Main findings

Estimates of equation (1) indicate that log income is not associated with increased mental healthcare use when other economic factors are omitted (Column 1, Table 2) and when financial difficulties and educational attainment are simultaneously included (Columns 2 and 3, Table 2). Notably, the coefficient on income is both economically and statistically insignificant. For example, the point estimate with the largest magnitude equals -0.007 (Column 3), suggesting that a 100% increase in income reduces mental healthcare use by only 0.7 percentage points. In subsequent analyses, we confirm this null finding with different parameterisations of income. Similarly, there is no evidence that having financial difficulties – not having money to pay bills on time – is associated with mental healthcare use, conditional on need. Each coefficient estimate is small and statistically insignificant.

In contrast, the results in Column 3 of Table 2 indicate a strong positive association with educational attainment. University graduates with poor mental health are 4.6 percentage points more likely to receive mental healthcare in the next 12 months than high school dropouts (equivalent to a 41% increase relative to the sample mean). High school graduates and people with a post-school diploma or trade certificate are also significantly more likely to receive mental healthcare than high school dropouts (2.5 and 1.9 percentage points, respectively).

The final column of results (Column 4) is based on a sample of people with poor mental health who did not report mental healthcare use when previously asked (i.e. 4 years ago). This further reduces any bias due to inter-temporal dependencies or persistence in mental health and healthcare use. The sample is reduced because conditioning on lagged healthcare means that the first wave is omitted. As expected, the sample mean of the outcome is lower (9.6%), but importantly, the results for log income, financial difficulties and educational attainment are quantitatively similar. For instance, the estimated 'university degree' coefficient equals 0.034, which is a 35% increase relative to the sample mean (compared with 41% in Column 3).

Conversely, if we include individuals who report having a serious long-term mental illness (which are excluded from the main sample), then the sample mean of the outcome is higher (15.4%), and the estimated education coefficients are larger (see Appendix Table A1).[3] The 'university degree', 'high school grad' and 'diploma/certificate' coefficients are estimated to equal 5.5, 3.4 and 3.0 percentage points, respectively. However, relative to the sample mean, the estimated percent increase in mental healthcare use is slightly smaller than in the main sample (e.g. 36% higher for university graduates compared with 41% in Table 2).

The full set of estimates corresponding to the regressions in Table 2 are provided in Appendix Table A2. These show a strong positive association between mental healthcare use and being female and

[3] Adding individuals with a serious long-term mental illness, who have poor mental health (MHI-5 < 68), leads to the inclusion of 1246 observations to the estimation sample (11% of the larger sample of 11,022 observations). The sample mean of mental healthcare use for this group equals 47.4%, which is substantially larger than the 11.3% for the main sample. This much higher rate is because these individuals report having a doctor diagnosed mental illness, and therefore by definition have already received mental health-related care (though not necessarily from a psychologist or psychiatrist).

younger aged. The estimates also show that higher scores for the ‘social functioning’, ‘role emotional’ and ‘mental health’ dimensions of the SF-36 are negatively associated with mental healthcare use. Even though we focus on a sample with poor mental health, people with severe symptoms (very low scores) are more likely to seek mental healthcare.

Our main finding of a small income gradient and a large positive education gradient holds for various population subgroups. Log income coefficient estimates from regressions estimated separately by gender, age (21-35, 36-50, 51+), region of residence (metropolitan, regional/remote), and year of mental healthcare use (2009, 2013, 2017) are presented in Figure 3. Similar estimates for university degree are presented in Figure 4. The results show that household income is a statistically insignificant predictor of mental healthcare use (conditional on need) for 9 of the 10 subsamples. Conversely, 9 of the 10 university degree coefficients are statistically significant. The largest coefficient estimate equals 0.066 for people aged 21-35 years, indicating that university graduates in this age group with poor mental health are 6.6 percentage points more likely to use mental healthcare in the following 12 months than similar high school dropouts (relative to a sample mean of 14.9%). The largest coefficient estimate relative to its subgroup sample mean is for people aged >50, equalling a 54% increase (the sample mean for this subgroup is unusually low at 6.9%).

4.3. Robustness tests

In this subsection, we explore whether the findings in Table 2 are robust to using different approaches to control for need and to alternative measures of income. We begin with the former by re-estimating regression equation (1) using samples based on different MHI-5 cut-offs. The main estimation sample included people with an MHI-5 score of less than 68. In Columns 1-4 of Table 3, we present regression results for samples with scores < 50, < 60, < 70 and < 80, and in Column 5 results for the total sample. Across all these cutoffs, we continue to find weak associations between mental healthcare use and household income and financial difficulties. Conversely, we find that education is an important predictor for each sample. Across the columns, the coefficient for university degree is large and the percent effects (relative to the sample mean) are reasonably similar: 28%, 35%, 41%, 34% and 35% for columns 1 to 5, respectively.

Another approach to controlling for mental healthcare needs is using people’s scores on the Kessler Psychological Distress Scale (K10), which is available in waves 7, 11 and 15. Specifically, we include K10 score fixed-effects (i.e. an indicator for each K10 score) in addition to all the covariates from the primary specification. The estimates from this regression are very close to those in Table 2. Coefficient estimates for log income and financial difficulties equal -0.005 and -0.003 (p-values equal 0.48 and

0.68), and the coefficient estimates for educational attainment (university, high school graduate and diploma) equal 0.046, 0.024 and 0.020 (see Appendix Table A3). These estimates and those in Table 2 suggest that the estimated SES associations are not biased from uncontrolled need.

We also test the robustness of our finding of a near-zero income gradient. First, we allow for a more flexible functional form by replacing log income in our main regression specification (corresponding to Column 3 of Table 2) with income quintile indicator variables. The results in Figure 5 provide no evidence of a positive association between income and mental healthcare use: the coefficient estimates have negative signs, are relatively small in magnitude, and are not statistically significant at the 5% level.

Table 4 similarly demonstrates the robustness of our main income result by presenting estimates from regressions with alternative income and financial difficulties variables. First, we use variables measured one year before the measurement of mental health. Second, we use a more permanent measure by taking the median values over waves 2001-2007 (i.e. all before the first mental health measurement). Third, we use the median in the three waves before each measurement of mental healthcare use. These three alternatives reduce the likelihood that mental health problems are causing lower income and greater financial difficulties. They also reduce the likelihood that randomly occurring shocks in transitory income (but not permanent income) are attenuating the income coefficient estimate. While the samples for each model differ, there is considerable robustness. The coefficients on household income and financial difficulties remain small and statistically insignificant, while the estimates for educational attainment continue to show that having a university degree is a strong predictor of greater mental healthcare use.

5. Within-individual analysis

A limitation of the between-individual analysis is the potential for the estimated SES associations (α_1) to reflect unobserved characteristics. Therefore, we use the panel aspect of HILDA to provide estimates from regressions with individual fixed-effects. Specifically, we estimate how mental health 'shocks' that occur over time are associated with mental healthcare use, and whether income, financial difficulties and educational attainment moderate this association. This approach is represented by:

$$mhcare_{i,t} = \beta_1 mh_{it} + \beta_2' Z_{it} + \sum_{k=1}^{5} \beta_3^k mh_{it} \cdot Z_{it}^k + \beta_4' W_{it} + \beta_5' H_{it} + \delta_i + \lambda_t + \upsilon_{i,t} \qquad (2)$$

Where mh_{it} is either a person's reversed MHI-5 score or a binary indicator of having poor mental health (MHI-5 < 68), W_{it} is a set of time-varying demographic characteristics, H_{it} is a set of healthcare need variables, δ_i is an individual fixed-effect, and λ_t is a time fixed-effect.

Our SES measures differ slightly from those used above. The SES variables included separately (Z_{it}) and interacted with mental health ($mh_{it} \cdot Z_{it}^k$) are indicators of: household income in the lowest quartile, financial difficulty, and university education. This change has been made to ease the interpretation of the coefficients on the interaction terms (β_3^k). Z_{it} also includes gender (female) and age (≤ 45) indicators. These two non-SES terms are included because they significantly predict mental healthcare use (see Appendix Table A2) and are associated with the SES variables. In other words, these terms are included because age and gender are likely to moderate the association between mental health (shocks) and healthcare use, and we want to avoid attributing this to SES.

Another difference from the Section 4 analysis is the estimation sample. Previously, we restricted the sample to people with poor mental health (MHI-5 < 68). However, this restriction is inappropriate for the fixed-effects analysis. The β_1 and β_3^k parameters in equation (2) are identified from within-individual across-time variation (i.e. changes or shocks) in people's mental health.[4] We remove this variation if we restrict the sample to only those with poor mental health in every wave. Instead, our sample includes all people who report poor mental health in at least one wave (2008, 2012 or 2016). This restriction implies that the key parameters are identified primarily from mental health changes in the left-hand side of the distribution, such as from moderate to poor mental health. Conversely, we limit identification stemming from mental health changes in the right-hand side of the distribution, which are not usually associated with mental healthcare use. Another change to the estimation sample is we include people reporting a long-term mental illness. Excluding such people, as we did for the analyses reported in Section 4, would eliminate the reasonable situation in which a negative shock to mental health becomes a long-term condition.[5]

Estimates of β_1 and β_3^k are shown in Table 5. Given the inclusion of interaction terms, the first row of results are the associations between poor mental health and mental healthcare for people who are male, aged > 45, not low income, without financial difficulties, and not university educated. The estimates for the (reversed) continuous MHI-5 score (Column 1) and the binary indicator of poor mental health (Column 2) are both small in magnitude and statistically insignificant. This result

[4] Note β_3^k is not primarily driven by within-individual variation in SES, which changes little over time. Instead, it is driven by within-individual variation in mental health.

[5] The estimation results are similar to those reported in Table 5 if people with a long-term mental illness are excluded from the sample.

suggests that older, less educated men do not increase their mental healthcare use following negative mental health changes.

The interaction terms in Table 5 show that a worsening in mental health is significantly associated with greater mental healthcare use among women and younger people, which aligns with the findings from the cross-sectional analysis. Also aligned with the previous section are the SES results. Estimates indicate that low household income and financial difficulties do not significantly moderate the association between mental health and mental healthcare use. Low-income people with financial difficulties are just as likely to seek mental healthcare following an adverse mental health shock as other people (ceteris paribus). Conversely, the interaction term between poor mental health and university education is significantly positive. Specifically, the association between poor mental health and mental healthcare use is 4.3 percentage points higher if the person has a university degree than if they do not (Column 2 in Table 5). In other words, the individual fixed-effects estimates in Table 5 suggest strong horizontal inequity by educational attainment.

6. Exploring mental health medication use

The primary focus of this study is horizontal inequity in the use of mental health professionals, such as psychologists and psychiatrists. This focus aligns with Australian clinical practice guidelines, which recommend psychological management as the appropriate first-line treatment for mild to moderate mood disorders (Malhi et al., 2018). However, many people receive prescription mental health medication without receiving psychological therapy. Consequently, the positive education gradient in the use of mental health professionals may be (partly) offset by a negative education gradient in the use of medication. In this Section, we test this possibility by exploring mental health medication use.

Information on medication use is contained in the 'Serious Illness Conditions' module of HILDA's wave 9, 13 and 17 questionnaire. Respondents are asked whether they have a doctor-diagnosed medical condition that has lasted or is likely to last for six months or more, and if they answer yes, they are asked whether they take any prescription medications for the condition and what the condition is, with depression or anxiety being a response option. We use this information to create a dependent variable indicating that the person is taking prescription medication for depression or anxiety.

A limitation of this measure is that we do not know when the person began taking medication. Given that the questions relate to serious ongoing conditions, a non-trivial proportion was likely prescribed medication before their need was measured in the waves 8, 12 and 16 HILDA interviews (raising endogeneity issues). Another limitation is that the medication question is only asked of people who view their mental health problem as a serious, long-term medical condition, leading to an overly low medication use rate of 4.1% in our full sample and 9.1% in our sample with MHI-5<68.[6]

Despite these limitations, we have replicated the Table 2 and Table 5 analyses with the medication outcome replacing the mental health professional outcome. We find small and statistically insignificant associations between educational attainment and medication use (see Appendix Table A4). For instance, the coefficient on university degree equals 0.004 (p-value = 0.648), implying that university graduates are 0.4 percentage points more likely to use mental health medication than high school dropouts. This compares with an estimate of 0.046 in Table 2. Similarly, we find a small and statistically insignificant coefficient on the interaction between university degree and mental health in the individual fixed-effects models. For the continuous index specification, the estimate equals -0.001 (p-value = 0.625), compared with 0.037 in Table 5.

The estimation results indicate that the pro-education inequity in the use of mental health professionals is not offset by relatively high medication use among the less educated. Instead, it appears that higher-educated people are relatively more likely to use a combination of therapy and medication, while lower-educated people are relatively more likely to use medication alone.

7. Exploring the education gradient

7.1. Field of Study

The estimated association between educational attainment and the use of mental health professionals has been consistently large (see Sections 5 and 6). While several proposed mechanisms link education to health and health-behaviours, the most direct pathway is increased knowledge (Grossman, 1972; Kenkel, 1991; Cutler and Lleras-Muney, 2010). Individuals with greater health-related knowledge may make more efficient health production decisions, communicate more effectively with healthcare providers, obtain increased health benefits from the same number of inputs, and have higher compliance with medical instructions (Johnston et al., 2015). In this Section, we explore the ‘education gradient’ and the potential importance of health-specific knowledge by testing whether the education association is larger for people with a health-related post-school qualification. This analysis relates to the literature exploring the impacts of having a medical degree on health and health-related behaviours;

[6] The annual prevalence of antidepressant use in 2019 equalled 170.4 per 1000 women and 101.8 per 1000 men (de Oliveira Costa et al., 2023).

for recent examples, see Frakes et al. (2021), Finkelstein et al. (2022) and Anderson et al. (2023). The evidence from the literature is mixed, with positive, negative and near-zero estimated effects of medical knowledge on health outcomes.

In the HILDA survey, people are asked questions about their highest formal educational qualification since leaving school, including the "main field of study of that qualification". Responses are grouped into 14 broad categories: natural and physical sciences; information technology; engineering; architecture; agriculture and environment studies; medicine; nursing; other health-related; education; management and commerce; law; society and culture; creative arts; and food and hospitality. The fields of study that likely contain instruction on mental health and healthcare or help people navigate the healthcare system are medicine, nursing, other health-related, and society and culture. The latter is included because this category contains qualifications in psychology and social work (and were specific examples provided to respondents).

Table 6 presents estimates based on the main regression specification with field-of-study variables added, using an estimation sample comprising respondents in poor mental health who report receiving a post-school qualification (of any type) and answering the field-of-study question. Column (1) includes only the four health-related fields, meaning the estimated associations are relative to mental healthcare use among people with non-health qualifications. Column (2) includes all fields apart from 'natural and physical sciences', which is the reference category. Notably, we continue to find that the estimate for university education is large, while the estimates for household income and financial difficulties remain small and statistically insignificant.

The first main finding in Table 6 is that people with a medical degree have significantly lower rates of mental healthcare use than people with non-health-related qualifications. The estimate in Column (1) suggests that mental healthcare rates among medical degree holders is 6.8 percentage points lower. A potential explanation is the reluctance to seek help given the potential complexities (including stigma) of a 'doctor becoming a patient' (Brooks et al., 2011). The finding of a negative association with medical qualifications aligns with results in some past studies. For example, Finkelstein et al. (2022) find that access to medical expertise, defined as being a doctor or having one in the close family, is generally associated with poorer adherence to medication guidelines.

The second main finding of Table 6 is that people with qualifications in the 'society and culture' category are estimated to have significantly higher rates of mental healthcare: 3.3 percentage points in Column 1 and 5.9 percentage points in Column 2. Unfortunately, it is not possible to further explore this finding by disaggregating the 'society and culture' category. However, a likely explanation for the significant positive association is that there are people in this group who have studied psychology, social work, or other social topics, and therefore have had more exposure to mental health issues and are less likely to have stigmatised views of mental illnesses and their treatments. It is also likely that people who select these qualifications are interested in and positively disposed towards mental healthcare. Other fields of study including Creative Arts and Law have similarly large coefficient estimates, however these are imprecisely measured and thus we refrain from interpreting these results.

7.2. Potential mediators and confounders

In the final empirical section, we investigate whether we continue to find horizontal inequity by education when we include additional individual characteristics that are known to be correlated with education and health-related behaviours; namely, personality, social support and economic preferences. The set of continuous personality variables includes external Locus of Control, which measures the extent that people believe they can control events that affect their lives, and the Big-5 Personality Inventory: extraversion, agreeableness, conscientiousness, openness to experience, and emotional stability. Social support is represented by two binary variables indicating that the person agrees they 'have no one to lean on in times of trouble' and 'don't have anyone that they can confide in'. Finally, we include proxies for (financial) risk and time preferences. These are based on responses to questions about the 'amount of financial risk that you are willing to take with your spare cash' and about the time period that is most important when 'planning your saving and spending'.

In Table 7, we supplement the main mental healthcare between-individual specification (corresponding to Column 3 of Table 2) with these 10 additional variables. The estimates indicate that 'agreeableness' (i.e. cooperative, kind, sympathetic, and warm) and 'openness to experience' (i.e. complex, creative, imaginative, intellectual, and philosophical) are significant positive predictors of mental healthcare use, and 'conscientiousness' (i.e. organised, efficient, orderly, systematic) is a significant negative predictor, conditional on need. Table 7 also shows that having no one to lean on in times of trouble, which could involve financial assistance and practical or emotional support, is associated with a 2.3 percentage point lower likelihood of mental healthcare use.

Most notably, Table 7 shows that including these characteristics reduces the difference in mental healthcare use between university graduates and high school dropouts from 4.6 percentage points (Column 3, Table 2) to 3.0 percentage points. Despite this 35% decrease in the magnitude of the university coefficient, it remains the strongest predictor of mental healthcare use (conditional on need).

8. Conclusion

There is a long history of testing for horizontal equity in healthcare. This paper provides new evidence on mental healthcare, for which relatively little research exists. Mental healthcare is an important dimension to evaluate because the determinants of inequity may differ from those for other healthcare types. For instance, stigma is likely more consequential for the treatment of depression than cardiovascular disease. Our context is Australia, where there are shortages of mental health professionals, and many people in need are unable to access care (Productivity Commission Inquiry, 2020; Victorian Royal Commission, 2021).

Our empirical approach focuses on people who are currently experiencing symptoms of poor mental health, but without a pre-existing mental illness or disability, and tests for socioeconomic inequity in the use of mental health professionals within the next 12 months. A person's socioeconomic position is characterised by household income, the experience of financial difficulties, and educational attainment. Notably, we compare people residing in the same local area who face the same potential supply of mental health services.

While we expected to find that ability-to-pay was of primary importance (Callander et al., 2017), we did not find that respondents with low household income or financial difficulties are less likely to use mental healthcare services, conditional on the need for and availability of services. In contrast, we find evidence of a strong education gradient: people with a university degree are around 50% more likely to see a mental health professional than high school dropouts in the 12 months following a newly developed mild or moderate mental disorder. These results are robust to using alternative income measures and regression specifications, and to controlling for personality, social support and economic preferences. Estimates from individual fixed-effects specifications also support these results. Specifically, the association between poor mental health and mental healthcare use is 4.3 percentage points higher if the person has a university degree than if they do not. These findings support a previously observed link between education and mental health help-seeking in the Canadian Community Health Survey (CCHS). The study found a strong education – but not income – gradient in mental healthcare service use (Steele et al., 2007). Similarly, in a Dutch population, higher education predicts more mental healthcare use, while lower education is linked with more primary care use (ten Have et al., 2003).

Additional analyses indicate that the higher mental healthcare use among people with university qualifications, conditional on need, is particularly apparent for people with qualifications in 'society and culture'. This category includes psychology and social work qualifications, suggesting that people with greater knowledge of and less stigmatised attitudes toward mental health are more likely to use needed mental healthcare. To verify this correlational observation, causal studies estimating the effects of receiving mental health-related instruction are required.

There are a few noteworthy limitations of our analyses. First, the data allows us to explore the extensive margin but not the intensive margin of mental healthcare use. Therefore, we cannot comment on SES inequities in the number of mental health services used after the initial visit. It is possible that income is more important at this margin – i.e. that low educational attainment reduces the likelihood that someone seeks mental healthcare, and low income constrains the number of services someone can purchase once they have begun treatment. However, a recent study by Black et al. (2024) finds that this is not the case for child mental healthcare use in Australia. Large income inequities were found at the extensive margin, but not at the intensive margin. A related limitation is that we cannot explore differences in the mix of service providers (e.g. differences across clinical psychology, general psychology, psychiatry, social work, etc.). It seems likely that demand for different providers could differ by SES.

A third limitation is that our findings do not inform on horizontal inequity in mental healthcare use among people suffering from severe mental disorders (such as schizophrenia, bipolar disorder, and borderline personality disorder). People with severe disorders are under-represented in survey data, and in addition, our analysis relies on responses to a standard mental health scale that is unable to measure the complex mental healthcare needs of people with severe disorders. Fourth, the mental health and healthcare information is self-reported and may contain non-random measurement error. For example, people with greater educational attainment may be more likely to self-report mental health problems due to less social stigma and discrimination, leading to downward biased estimates of the association between education and mental healthcare use, conditional on having a mental health problem (i.e. differences by educational attainment may be even larger than those presented).

In summary, we find no evidence of income-related inequity in the use of mental health professionals among people with poor mental health. However, clear horizontal inequity exists by educational attainment. This suggests that to reduce inequities in mental healthcare use, further consideration should be given to policies that target lower-educated populations, support the development of mental health literacy, and address the longstanding issue of stigma.

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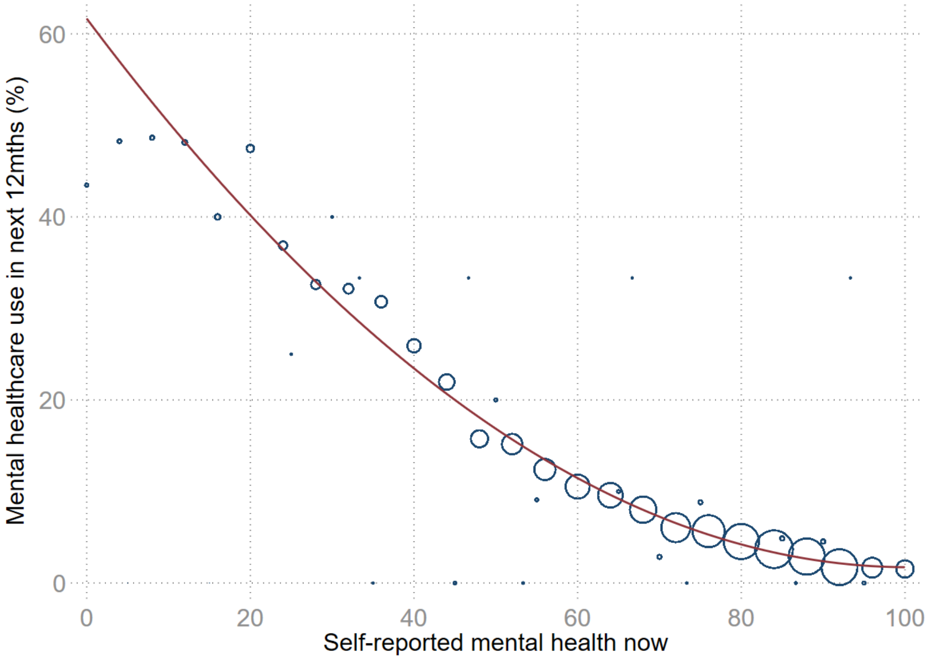
FIGURES

Figure 1: Association between mental healthcare use (*t+1*) and mental health (*t*)



Note: Circles represent mean healthcare use for a specific value of self-reported mental health. Circle size is representative of number of observations.

Figure 2: Mental healthcare use by income and education, for those with poor mental health

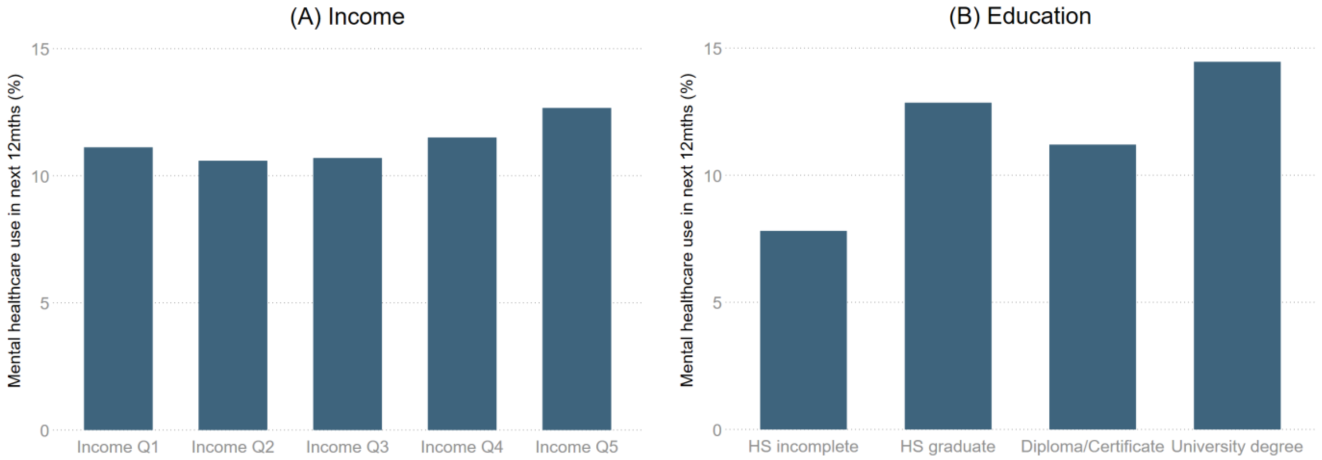
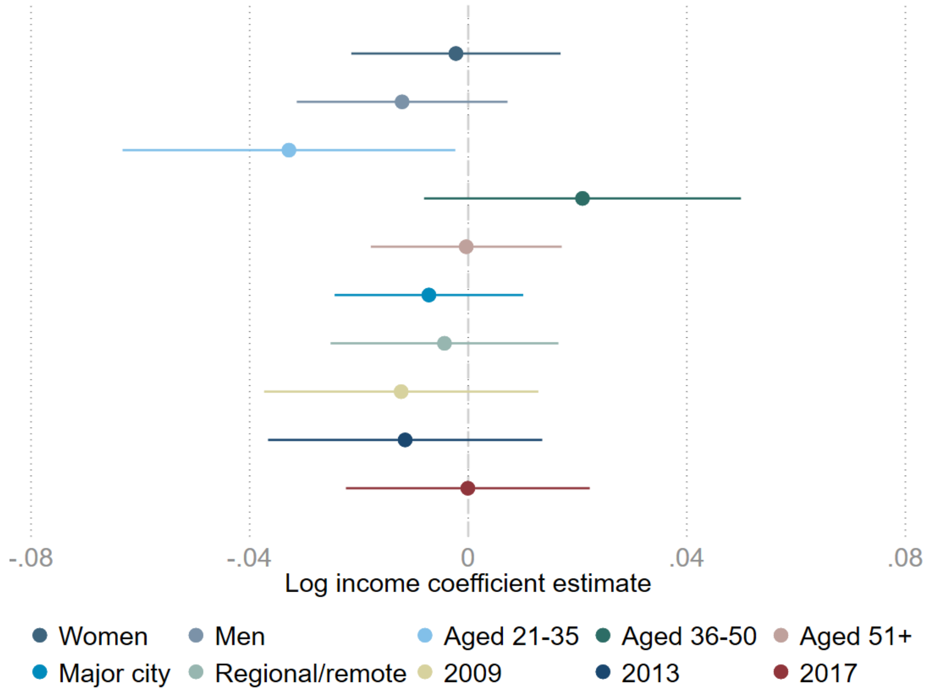
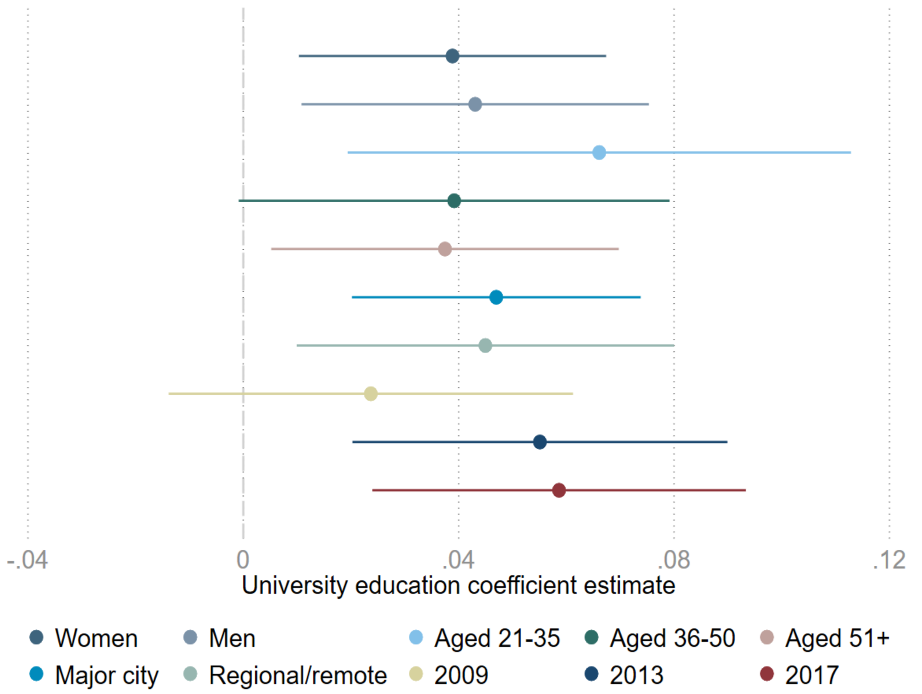


Figure 3: Log household income coefficient estimated separately using ten subgroups



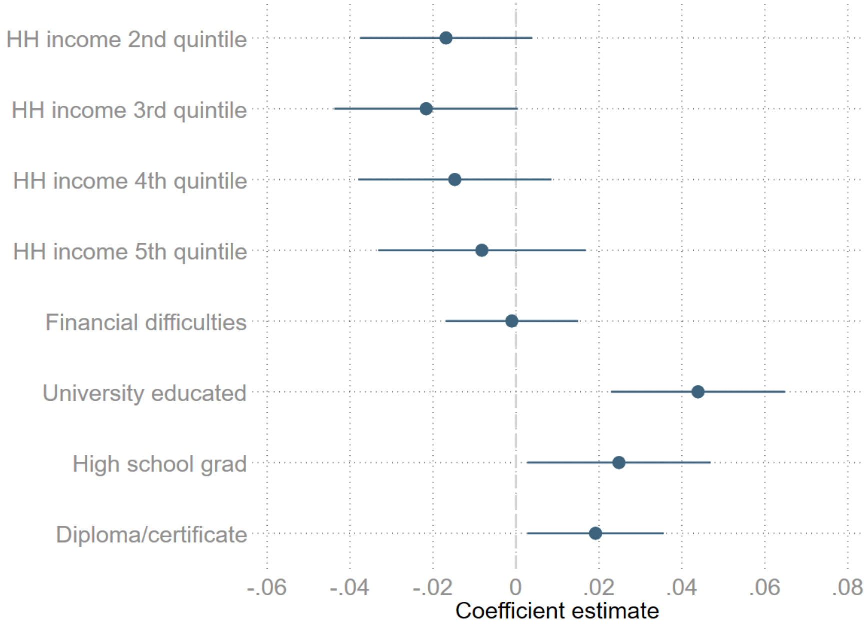
Note: Plotted points are estimated coefficients on log household income variable, based on the specification in Col 3 of Table 2. 95% confidence intervals expressed with horizontal lines.

Figure 4: University degree coefficient estimated separately using ten subgroups



Note: Plotted points are estimated coefficients on university education variable, based on the specification in Col 3 of Table 2. 95% confidence intervals expressed with horizontal lines.

Figure 5: Coefficient estimates allowing for nonlinear associations with household income



Note: Plotted points are estimated associations based on a version of the specification in Col 3 of Table 2, with log income replaced with quintile dummy variables (lowest quintile omitted / comparison category). 95% confidence intervals expressed with horizontal lines.

TABLES

Table 1: Sample means for key variables

	Full Sample (1)	Poor mental health sample (2)
Log household income	10.7	10.6
Financial difficulties	0.17	0.28
Education: University	0.29	0.25
Education: High school grad	0.13	0.14
Education: Diploma/certificate	0.34	0.34
Male	0.47	0.43
Age	46.7	45.3
Married or cohabitating	0.72	0.66
Separated or divorced	0.09	0.12
Widowed	0.03	0.04
Never married	0.15	0.19
Number of children	0.56	0.56
Speak non-English language	0.10	0.12
SF-36 Physical functioning	85.0	78.2
SF-36 Role-physical	80.9	67.8
SF-36 Bodily pain	73.3	63.4
SF-36 General health	69.0	57.0
SF-36 Vitality	60.7	44.4
SF-36 Social functioning	84.3	67.5
SF-36 Role emotional	85.9	65.3
SF-36 Mental health (MH5)	75.4	55.3
Long-term health condition	0.23	0.32

Notes: Presented figures are sample means. Variables are binary except for log income, age, and the eight SF-36 health dimensions. The Column 1 sample is aged 21-79, with non-missing information, and without a long-term serious mental health condition (N = 32,301). The Column 2 sample imposes the additional restriction of having MHI-5<68 and is the main estimation sample used in Section 4 (N = 9,776).

Table 2: Associations between SES and mental healthcare use for sample with need

	(1)	(2)	(3)	(4)
Log household income	-0.000	-0.001	-0.007	-0.001
	(0.007)	(0.007)	(0.007)	(0.009)
Financial difficulties		-0.005	-0.001	0.008
		(0.008)	(0.008)	(0.011)
Education: University degree			0.046^{***}	0.034^{***}
			(0.011)	(0.013)
Education: High school grad			0.025^{**}	0.025^{*}
			(0.011)	(0.014)
Education: Diploma/certificate			0.019^{**}	0.018^{*}
			(0.008)	(0.010)
Demographics covariates	Y	Y	Y	Y
Health covariates	Y	Y	Y	Y
Area (SA3) fixed-effects	Y	Y	Y	Y
Omit observations with past use	N	N	N	Y
Outcome sample mean	0.113	0.113	0.113	0.096
Number of observations	9776	9776	9776	5277

Notes: Dependent variable in each regression is an indicator for whether the person saw a mental health professional, such as a psychiatrist or psychologist, sometime during the next 12 months. Demographic covariates include dummy variables for gender, age, marital status, number of children, country of birth, non-English language spoken at home, and survey wave. Health covariates include all 8 SF-36 subscales, and dummy variables for 15 long-term health conditions. Standard errors clustered at the individual level shown in parentheses.

Table 3: Robustness to using samples based on different mental health cut-offs

	MHI-5 ≤ 50 (1)	MHI-5 ≤ 60 (2)	MHI-5 ≤ 70 (3)	MHI-5 ≤ 80 (4)	Unrestricted MHI-5 (5)
Log household income	-0.000	-0.010	-0.006	-0.004	-0.002
	(0.017)	(0.009)	(0.007)	(0.004)	(0.003)
Financial difficulties	-0.007	-0.004	-0.001	-0.006	-0.001
	(0.019)	(0.011)	(0.008)	(0.006)	(0.004)
Education: University	0.052^{*}	0.047^{***}	0.046^{***}	0.028^{***}	0.020^{***}
	(0.028)	(0.014)	(0.011)	(0.007)	(0.004)
Education: High school grad	-0.000	0.028^{*}	0.025^{**}	0.018^{**}	0.013^{***}
	(0.029)	(0.016)	(0.011)	(0.007)	(0.005)
Education: Diploma/certificate	0.002	0.016	0.019^{**}	0.016^{***}	0.012^{***}
	(0.022)	(0.011)	(0.008)	(0.005)	(0.004)
Outcome sample mean	0.184	0.134	0.113	0.082	0.057
Number of observations	2533	6255	9801	18649	32301

Notes: Dependent variable is an indicator for whether the person saw a mental health professional sometime during the next 12 months. Regression specification is identical to that shown in column (3) of Table 2. Standard errors clustered at the individual level shown in parentheses

Table 4: Associations using different definitions of income and financial difficulties

	Year prior to MHI-5 measurement (1)	Median from waves 2001-2007 (2)	Median from 3 waves prior to healthcare use (3)
Log household income	0.008	0.003	0.000
	(0.007)	(0.010)	(0.008)
Financial difficulties	-0.002	-0.010	-0.004
	(0.009)	(0.011)	(0.009)
Education: University degree	0.040***	0.031**	0.042***
	(0.011)	(0.012)	(0.011)
Education: High school grad	0.021*	0.027**	0.024**
	(0.012)	(0.013)	(0.011)
Education: Diploma/certificate	0.016*	0.019*	0.017**
	(0.009)	(0.010)	(0.008)
Outcome sample mean	0.114	0.107	0.113
Number of observations	9431	7240	9857

Notes: Dependent variable in each regression is an indicator for whether the person saw a mental health professional, such as a psychiatrist or psychologist, sometime during the next 12 months. Figures are estimated associations based on a version of the specification in Col 3 of Table 2, with log income and financial difficulties replaced with alternative versions. In column (1), values from waves 7, 11 and 15 are used. In column (2), median of values from waves 1-7 are used. In column (3), median of values from waves 6-8, 10-12, and 14-16 are used. Standard errors clustered at the individual level shown in parentheses.

Table 5: Within-individual association between mental health and mental healthcare use

	Continuous MH Index (1)	Binary MH Indicator (2)
Poor mental health measure	0.011	-0.001
	(0.008)	(0.010)
Interaction terms		
Female	0.016*	0.032***
	(0.008)	(0.012)
Age ≤ 45	0.027***	0.021*
	(0.008)	(0.011)
Low income	-0.005	-0.014
	(0.011)	(0.015)
Financial difficulties	0.008	0.013
	(0.011)	(0.017)
University education	0.037***	0.043***
	(0.010)	(0.015)
Outcome sample mean	0.119	0.119
Number of individuals	4355	4355
Number of observations	11492	11492

Notes: Figures from individual fixed-effects regressions using sample from three HILDA waves who have poor mental health in at least one of the three included waves. The standardised poor mental health index is the MHI-5 standardised to have a mean of zero and a standard deviation of one, and reversed so that it is increasing in worse mental health. Regressions include same covariates included in column (3) of Table 2, plus individual fixed-effects, and log income and financial difficulties defined as median of values from waves 1-7. Standard errors clustered at the individual level shown in parentheses.

Table 6: Associations between field of study of highest qualification and mental healthcare use

	(1)		(2)	
Log income	0.001	(0.009)	0.002	(0.008)
Financial difficulties	0.001	(0.011)	-0.001	(0.011)
Education: University	0.047^{***}	(0.015)	0.044^{***}	(0.015)
Education: High school grad	0.017	(0.019)	0.014	(0.019)
Education: Diploma/certificate	0.010	(0.014)	0.008	(0.014)
Field: Medicine	-0.068^{**}	(0.028)	-0.044	(0.035)
Field: Nursing	-0.015	(0.017)	0.012	(0.028)
Field: Other health-related	-0.007	(0.020)	0.019	(0.029)
Field: Society and culture	0.033^{**}	(0.017)	0.059^{**}	(0.027)
Field: Information technology			0.021	(0.032)
Field: Engineering			0.004	(0.025)
Field: Architecture			-0.001	(0.028)
Field: Agriculture & environment			0.024	(0.034)
Field: Education			0.035	(0.027)
Field: Management & commerce			0.014	(0.024)
Field: Law			0.057	(0.042)
Field: Creative arts			0.056^{*}	(0.030)
Field: Food & hospitality			0.028	(0.028)
Observations	6438		6438	

Notes: Dependent variable in each regression is an indicator for whether the person saw a mental health professional, such as a psychiatrist or psychologist, sometime during the next 12 months. Demographic covariates include dummy variables for gender, age, marital status, number of children, country of birth, non-English language spoken at home, and survey wave. Health covariates include all 8 SF-36 subscales, and dummy variables for 15 long-term health conditions. The omitted reference category for column (2) is natural and physical sciences. Standard errors clustered at the individual level shown in parentheses.

Table 7: Associations between personality, social support and economic preferences and mental healthcare use

Log income	-0.005	(0.007)
Financial difficulties	-0.000	(0.009)
Education: University	0.030***	(0.011)
Education: High school grad	0.014	(0.011)
Education: Diploma/certificate	0.012	(0.009)
External locus of control index	-0.001	(0.005)
Big-5: Extroversion	0.000	(0.004)
Big-5: Agreeableness	0.011***	(0.004)
Big-5: Conscientiousness	-0.012***	(0.004)
Big-5: Emotional stability	-0.005	(0.004)
Big-5: Openness to experience	0.020***	(0.004)
No one to confide in	-0.013	(0.009)
No on to lean on in times of trouble	-0.023**	(0.010)
Risk averse financially	0.003	(0.007)
Short planning horizon	-0.003	(0.007)
Number of observations	9437	

Notes: Regression specification is same as used in column (3) of Table 2, aside from the additional variables shown. Locus of control and Big-5 personality measures are standardised to have a mean of zero and a standard deviation of one. Social support and economic preference variables are binary. Standard errors clustered at the individual level shown in parentheses.

Supplementary Appendix

Figure A1: Distribution of SF-36 Mental Health Score

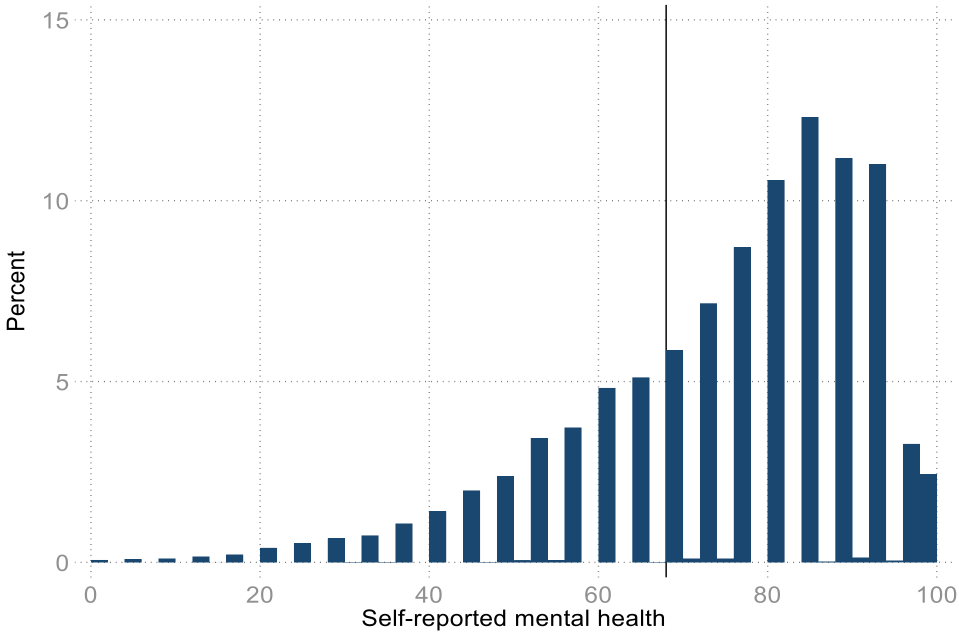


Table A1: Estimates corresponding to Table 2, using a larger sample that includes people with a long-term mental illness

	(1)	(2)	(3)	(4)
Log household income	0.008	0.006	0.000	0.001
	(0.007)	(0.007)	(0.007)	(0.009)
Financial difficulties		-0.009	-0.005	0.008
		(0.008)	(0.008)	(0.011)
Education: University degree			0.055***	0.044***
			(0.011)	(0.013)
Education: High school grad			0.034***	0.029**
			(0.012)	(0.015)
Education: Diploma/certificate			0.030***	0.029***
			(0.009)	(0.011)
Demographics covariates	Y	Y	Y	Y
Health covariates	Y	Y	Y	Y
Area (SA3) fixed-effects	Y	Y	Y	Y
Omit observations with past use	N	N	N	Y
Outcome sample mean	0.154	0.154	0.154	0.119
Number of observations	11022	11022	11022	5750

Notes: Dependent variable in each regression is an indicator for whether the person saw a mental health professional, such as a psychiatrist or psychologist, sometime during the next 12 months. Demographic covariates include dummy variables for gender, age, marital status, number of children, country of birth, non-English language spoken at home, and survey wave. Health covariates include all 8 SF-36 subscales, and dummy variables for 15 long-term health conditions. Standard errors clustered at the individual level shown in parentheses.

Table A2: Estimates corresponding to Table 2

	(1)	(2)	(3)	(4)
Log household income	-0.000	-0.001	-0.007	-0.001
	(0.007)	(0.007)	(0.007)	(0.009)
Financial difficulties		-0.005	-0.001	0.008
		(0.008)	(0.008)	(0.011)
Education: University			0.046***	0.034***
			(0.011)	(0.013)
Education: High school grad			0.025**	0.025*
			(0.011)	(0.014)
Education: Diploma/certificate			0.019**	0.018*
			(0.008)	(0.010)
Male	-0.040***	-0.040***	-0.040***	-0.038***
	(0.007)	(0.007)	(0.007)	(0.008)
Aged 30-39	-0.010	-0.010	-0.011	-0.037**
	(0.012)	(0.012)	(0.012)	(0.017)
Aged 40-49	-0.023*	-0.023*	-0.021*	-0.037**
	(0.012)	(0.012)	(0.012)	(0.017)
Aged 50-59	-0.065***	-0.066***	-0.063***	-0.081***
	(0.013)	(0.013)	(0.013)	(0.016)
Aged 60-69	-0.085***	-0.086***	-0.079***	-0.091***
	(0.015)	(0.015)	(0.015)	(0.019)
Aged 70-79	-0.108***	-0.109***	-0.101***	-0.102***
	(0.017)	(0.017)	(0.017)	(0.021)
Cohabitating (not married)	-0.013	-0.012	-0.010	-0.014
	(0.010)	(0.011)	(0.011)	(0.014)
Separated	0.026	0.027	0.027	0.024
	(0.018)	(0.018)	(0.018)	(0.023)
Divorced	0.004	0.005	0.005	0.000
	(0.013)	(0.013)	(0.013)	(0.016)
Widowed	0.001	0.001	0.003	0.008
	(0.016)	(0.016)	(0.016)	(0.021)
Never married	-0.005	-0.004	-0.004	-0.015
	(0.011)	(0.011)	(0.011)	(0.015)
Number of children	0.002	0.002	0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.006)
Speak non-English language	-0.029**	-0.030**	-0.031**	-0.016
	(0.013)	(0.013)	(0.013)	(0.016)
Wave 12	0.031***	0.032***	0.030***	
	(0.008)	(0.008)	(0.008)	
Wave 16	0.049***	0.049***	0.046***	0.008
	(0.008)	(0.008)	(0.008)	(0.008)
SF-36 Physical functioning	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 Role-physical	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 Bodily pain	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 General health	-0.000*	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 Vitality	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 Social functioning	-0.001***	-0.001***	-0.001***	-0.001***

	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 Role emotional	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
SF-36 Mental health (MH5)	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Long-term health condition	0.025**	0.025**	0.025**	0.003
	(0.012)	(0.012)	(0.012)	(0.015)
Condition: Sight problems	0.016	0.016	0.014	0.033
	(0.022)	(0.022)	(0.022)	(0.027)
Condition: Hearing problems	-0.001	-0.001	0.001	0.010
	(0.015)	(0.015)	(0.015)	(0.019)
Condition: Speech problems	-0.048	-0.048	-0.046	0.036
	(0.051)	(0.051)	(0.052)	(0.084)
Condition: Blackouts, fits	-0.034	-0.034	-0.033	-0.045
	(0.040)	(0.040)	(0.040)	(0.039)
Condition: Learning problem	-0.005	-0.005	0.001	-0.036
	(0.036)	(0.036)	(0.036)	(0.047)
Condition: Arms, fingers limitation	-0.023	-0.023	-0.024	-0.025
	(0.019)	(0.019)	(0.019)	(0.025)
Condition: Gripping things problem	0.014	0.014	0.016	0.028
	(0.020)	(0.020)	(0.020)	(0.025)
Condition: Feet, legs limitation	0.000	0.000	-0.000	0.009
	(0.015)	(0.015)	(0.015)	(0.018)
Condition: Restricts physical activity	-0.012	-0.012	-0.011	0.009
	(0.013)	(0.013)	(0.013)	(0.016)
Condition: Disfigurement	-0.009	-0.009	-0.005	0.063
	(0.042)	(0.042)	(0.042)	(0.062)
Condition: Breathing difficulties	-0.028*	-0.027*	-0.027*	-0.004
	(0.015)	(0.015)	(0.015)	(0.019)
Condition: Chronic pain	0.023*	0.023*	0.021	0.044***
	(0.014)	(0.014)	(0.014)	(0.017)
Condition: Head injury, stroke	0.024	0.024	0.023	-0.010
	(0.031)	(0.031)	(0.031)	(0.034)
Condition: Restrictive with treatment	0.002	0.002	0.001	-0.000
	(0.013)	(0.013)	(0.013)	(0.016)
Condition: Any other condition	-0.016	-0.016	-0.015	-0.025*
	(0.012)	(0.012)	(0.012)	(0.014)
N	9776	9776	9776	5277

Notes: Dependent variable in each regression is an indicator for whether the person saw a mental health professional, such as a psychiatrist or psychologist, sometime during the next 12 months. Country of birth fixed-effects and area fixed-effects omitted from table but included in regressions. Standard errors clustered at the individual level shown in parentheses.

Table A3: Specification with Kessler score fixed-effects included

Log household income	-0.005
	(0.007)
Financial difficulties	-0.004
	(0.009)
Education: University	0.046***
	(0.011)
Education: High school grad	0.024**
	(0.012)
Education: Diploma/certificate	0.020**
	(0.009)
Outcome sample mean	0.111
Number of observations	8649

Notes: Dependent variable is an indicator for whether the person saw a mental health professional sometime during the next 12 months. Regression specification is identical to that shown in column (3) of Table 2 apart from the inclusion of Kessler score fixed-effects. Standard errors clustered at the individual level shown in parentheses

Table A4: Associations between education and medication use

	Estimate	(s.e.)
Cross-sectional associations		
(1) University degree	0.004	(0.010)
High school grad	0.007	(0.011)
Diploma/certificate	-0.000	(0.009)
Within-individual associations		
(2) University degree x continuous MH Index	-0.003	(0.007)
(3) University degree x Binary MH Indicator	0.005	(0.010)

Notes: Dependent variable is an indicator for whether the person reports using prescription medication for depression or anxiety. Estimates are from three separate regressions: (1) Regression corresponding to Column 3 of Table 2; (2) Regression corresponding to Column 1 of Table 5; and (3) Regression corresponding to Column 2 of Table 5. Sample size in regression (1) equals 9,775. Sample size in regression (2) and (3) equals 11,489.