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ABSTRACT

Within the vast body of literature on the relationship between mental disorders and life satisfaction, no satisfactory treatment has been proposed to deal with the bi-directional relationship between the two. We estimate the causal effect of depression and anxiety on life satisfaction by applying an instrumental-variable regression approach to the Household, Income and Labour Dynamics in Australia (HILDA) survey. Our identification strategy exploits regional variation in the tendency to diagnose depression and anxiety, while also using an individual-level panel-data method. Our results show that previous research seriously overestimates the effect of depression and anxiety on life satisfaction. The most comparable estimate from previous research is over five times the size of our estimate. Furthermore, those papers that use such estimates to measure the monetary value of not suffering from depression or anxiety find it to be between $14 to $600 million a year per individual, compared to our estimate of around $60 thousand. Another source of bias which further inflates previous monetary estimates is the endogeneity of income. We account for this issue by using irregular sources of income, such as lottery winnings, instead of regular household income.

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A data appendix is available at
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1 Introduction

Mental disorders are receiving increased attention, with global burden of disease studies emphasizing that mental disorders are becoming one of the most serious health issues worldwide (Collins et al., 2011; Vigo et al., 2016; Whiteford et al., 2013). According to Vigo et al. (2016), the following mental disorders rank amongst the top 20 causes of global burden of disease: major depressive disorder (2^{nd}), anxiety disorders (7^{th}), schizophrenia (11^{th}), dysthymia (16^{th}), and bipolar disorders (17^{th}). Furthermore, major depression is expected to become the leading cause of the disease burden worldwide by 2030 (WHO, 2012). All mental disorders stated above are of major concern, but in this study, we limit our analysis to the top two in terms of global burden of disease, namely depression and anxiety.

In line with the global burden of disease studies, health economists have found a similar pattern using the compensating income variation method (CIV), namely that mental disorders rank among the top health conditions in terms of reduced well-being (Ásgeirsdóttir et al., 2017; Ásgeirsdóttir et al., 2019; Graham et al., 2011; Howley, 2017; Powdthavee and van den Berg, 2011). The CIV method involves estimating the amount of money that an individual would have to receive or give up to remain at the same level of well-being following a change in health status. However, only three such studies include mental disorders (Ásgeirsdóttir et al., 2017; Graham et al., 2011; Powdthavee and van den Berg 2011), and their results on mental disorders are likely over-estimated. The per-year CIV estimates for depression from Ásgeirsdóttir et al., (2017) and depression or anxiety from Powdthavee and van den Berg (2011) are $13,714,593 and $582,928,000 per year, respectively. Furthermore, Graham et al. (2011) estimates CIV for severe and moderate depression or anxiety to be 2.7- and 13.5-times the average income level. As pointed out by Ásgeirsdóttir et al. and Powdthavee and van den Berg, these extremely high numbers are likely a result of the untreated endogeneity of both mental health and income in the estimated subjective well-being equations. The income-endogeneity issue is well known in the subjective well-being literature but finding a robust instrument for income is challenging. However, a promising solution to the problem is to substitute regular household income for lottery winnings and other irregular sources of income (Ambrey & Fleming, 2014; Kim & Koh, 2021; Lindqvist et al., 2018).

The high correlation and bi-directional relationship between life satisfaction and mental health has made some economists reluctant to estimate the relationship between the two. Howley (2017) for example explicitly states that when calculating CIVs he does not include mental health due to the high correlation between subjective well-being and mental health and claims that mental health can be thought of as its own measure of well-being. These concerns are not unfounded given that an association has been found between poor self-reported life satisfaction and increased risk of mood disorders and suicide (DiTella et al., 1997; Helliwell, 2007; Koivumaa-Honkanen et al., 2001; Koivumaa-Honkanen et al., 2008). It has also been shown that poor long-term life satisfaction is a predictor of major depression (Rissanen et al., 2011). However, the question is not whether the two measures are related, which we know they are, but whether these correlations suggest that life satisfaction and mental health measure the same construct and could therefore be used interchangeably. If this is true, then the argument made by Howley (2017) would justify excluding mental health altogether from life satisfaction equations. However, the evidence suggests that this is not the case. For example, meta-analyses find that there are no significant gender differences in life satisfaction (Batz-Barbarich et al., 2018), yet there is evidence that women are twice as likely than men to experience depression (see e.g., Van de Velde et al., 2010). Routledge et al. (2016) also showed that high life-satisfaction scores do not necessarily coincide with the absence of mental disorders such as depression or anxiety. Furthermore, Powdthavee and van den Berg (2011) compare different measures of well-being, including life satisfaction and mental well-being, and find that the two produce significantly different results within the same data set. These findings are unsurprising, as there is robust evidence that life satisfaction is a global evaluation of an individual's entire life, while mental-health measurements usually are not (Powdthavee and van den Berg, 2011). The problem therefore is not that life satisfaction is measuring the same construct as mental health but rather that there exists a bi-directional relationship between the two that needs to be carefully considered in all subjective well-being equations that include measures of mental health.

In addition to the CIV studies that estimate the effect of mental disorders on life satisfaction there exists a substantial literature on this relationship within other areas of health economics and the field of psychology. Examples of such studies include applications from Great Britain (Layard et al., 2013), Germany (Beutel et al., 2010; Daig et al., 2009; Grabe et al., 2000; Layard et al., 2013), Australia (Layard et al., 2013), the Netherlands (Bergsma et al., 2011), Spain (Vázques et al., 2015), New Zealand (Fergusson et al., 2015), Canada (Lombardo et al., 2018; Stein and Heimber, 2004), and the U.S. (Adams et al., 2016). These studies use regression analyses, except for Bergsma et al. (2011), Grabe et al. (2000), and Stein and Heimber (2004) who utilize either correlation coefficients or mean comparisons. The results from these papers combined are in line with those from the CIV studies, indicating that there exists a strong negative relationship between mental disorders and life satisfaction. These estimates can, however, only infer correlation and not causation, because none of these papers solve the endogeneity problem of mental health in life satisfaction equations. Although researchers from those fields have not provided a satisfactory solution to this problem, they are aware of its existence. Fergusson et al. (2015), for example, formally tests the direction of causality between life satisfaction and mental health by estimating a structural equation model. They find clear evidence of a bi-directional relationship between the two. Furthermore, Beutel et al. (2010), Diag et al. (2009), and Vázquez et al. (2015) all suggest in some way that their results should be interpreted with caution because they do not adequately address causal pathways between mental health and life satisfaction. It is therefore clear that researchers in health economics and psychology are struggling with this issue and in need of a solution.

Although no papers have addressed the endogeneity problem of mental disorders in subjective well-being equations, studies exist that use instrumental-variable regression for mental health in other estimation equations. Duggan et al. (2005) estimate the effect of the use of second-generation antipsychotic drugs on health outcomes and spending on other types of medical care. As an instrument for treatment, they use psychiatrist's propensity to prescribe second-generation antipsychotic drugs. Another example is Dalsgaard et al. (2014) who estimate the effects of early intake of attention-deficit hypertension-disorder (ADHD) medication on key human-capital outcomes for children diagnosed with ADHD. As an instrument for treatment they utilize the variation in propensity to treat children with ADHD medication between hospitals, where the variation in propensity to treat comes from the difference in physician's tendency to prescribe ADHD medication to children.

Our approach to estimate the relationship between life satisfaction and depression or anxiety builds on the instrumental-variable methods of Duggan et al. (2005) and of Dalsgaard et al. (2014). The main idea behind their instrument is that the probability of receiving treatment depends on where people live, specifically, the propensity to treat at the hospital the individual attends, most likely close to their home. The hospital one attends might be endogenously determined, but individuals are unlikely to know the propensity to treat at that hospital, and therefore the propensity to treat assigned to the individual is likely exogenously determined. Utilizing this concept, we calculate the propensity to diagnose depression or anxiety in different geographic regions of Australia and use this variable as an instrument for those who have been diagnosed with depression or anxiety and are currently suffering from these illnesses.

We add to the literature on the relationship between life satisfaction and mental disorders in three ways. First, by analyzing data exceptionally well suited for the research question. Specifically, HILDA contains longitudinal individual-level data on both life satisfaction and mental-health disorders from 2001-2018, allowing us to tackle individual heterogeneity as well as the endogeneity of mental health in subjective well-being equations. To account for individual heterogeneity, we estimate our models using both random and fixed effects. To our knowledge only six population-based studies within the fields of economics and psychology have estimated the relationship between life satisfaction and mental health using longitudinal data (Ásgeirsdóttir et al., 2017; Bergsma et al., 2011; Fergusson et al., 2015; Layard et al., 2013; Lombardo et al., 2018; Powdthavee & van den Berg, 2011). Among the six papers that have studied this relationship using longitudinal data only Fergusson et al. (2015), Layard et al. (2013), and Powdhavee & van den Berg (2011) have utilized the panel structure of the data, by allowing for either random or fixed effects in their estimated models. Second, we estimate the effect of being diagnosed and suffering from depression or anxiety on life satisfaction accounting for the endogeneity of depression or anxiety by using the propensity to diagnose depression or anxiety by region over time as an instrument. This study therefore extends previous research by being the first to account for the bi-directional relationship between life satisfaction and mental health. Third, we estimate the CIV for depression or anxiety based on the results from our estimation to obtain a measure of the "intangible" costs associated with suffering from these mental disorders. We further improve endogeneity issues in previous CIV estimations by addressing the well-known problem of income endogeneity in subjective well-being equations. We do this by using lottery winnings and other irregular sources of income in our life satisfaction equation, rather than traditional income measures such as annual household income.

2 Empirical Framework

The dependent variable is standardized life satisfaction (W), with zero mean and variance one. We model life satisfaction primarily as a function of having a diagnosis and suffering from depression or anxiety (MH) and having windfall income (Y). In addition, we control for sociodemographic variables as well as wave dummies (X). Throughout the text we refer to MH as our treatment variable in a statistical sense, i.e., our treatment group corresponds to those who have been diagnosed and suffer from depression or anxiety, not to be confused with medical treatment of depression or anxiety. Formally, we model the relationship between life satisfaction and depression or anxiety as follows:

$$W_{it} = \theta MH_{it} + \delta Y_{it} + X_{it}\beta + \eta_i + \varepsilon_{it}, \tag{1}$$

where β represents a vector of parameters, θ and δ are parameters, and η denotes individual fixed effects. The error term is assumed to be iid normal, $\varepsilon_{it} \sim N(0, \sigma^2)$, where i denotes the individual and t represents the year.

The key problem when evaluating the effect of depression or anxiety on life satisfaction using a regression model is the endogeneity of depression or anxiety. There are multiple factors in the error term in a life satisfaction equation that could be correlated with depression or anxiety. These could be genetic risk factors, or adverse life experiences such as death of a loved one or interpersonal conflicts. It is simple to solve the endogeneity issues when it comes to time-invariant factors by simply applying fixed effects, but for individual time-variant factors the problem is more difficult to deal with. One way is to use an instrumental-variable regression. However, finding an instrument for depression or anxiety that satisfies the exclusion restriction in a life satisfaction equation is challenging. To try to achieve this we start by limiting our treatment variable to those who currently suffer from depression or anxiety but have also been diagnosed with either disorder at some point in their life. The exact definition of the diagnoses variable we use is: "Diagnosed with serious illness — Depression or anxiety". It should be noted that, by including only those who are suffering from depression or anxiety and have also be diagnosed, we end up with a treatment group that has significantly lower average life satisfaction, due to self-selection (further discussion on this matter is provided in the data section). However, this allows us to use the propensity to diagnose in different regions as an instrument for the treatment variable. This variable is highly correlated with our treatment variable and likely to satisfy the exclusion restriction, since the variation in the propensity to diagnose depression or anxiety by region mainly comes from differences in psychiatrist's or psychotherapist's tendency to diagnose depression or anxiety. Our instrument is therefore unlikely to be correlated with the error term in the life satisfaction equation.

With this definition of mental health we want to be careful that the comparison group doesn´t contain all those not in the treatment group; that is individuals that do not currently have depression or anxiety as well as those who have depression or anxiety but have never received a diagnosis. The inclusion of those suffering from undiagnosed depression or anxiety in the control group could lower the treatment effect. To address this issue, we drop those who suffer from depression or anxiety but have not been diagnosed, namely 26,535 observations corresponding to 3,446 individuals. Our comparison group therefore consists only of individuals who have not been diagnosed and are not suffering from depression or anxiety.

In addition to the model presented in Equation (1), i.e., the instrumental-variable regression with individual fixed effects (IV-FE), we estimate the relationship between life satisfaction and depression or anxiety in several different ways to determine how much of the bias in the OLS estimate comes from time-invariant individual effects and how severe the endogeneity bias of depression or anxiety actually is. Specifically, we estimate our model with OLS, RE, FE, IV, IV with RE, and IV with FE. Out of the six estimation strategies, the IV-FE model described in Equation (1) is preferred to the IV-RE because it is unlikely that our individual effects are uncorrelated with the error term.

It is important to note that since our instrument is the propensity to diagnose by region, the IV FE model is identified by changes over time in the propensity to diagnose in each region and those people who move across regions. In our sample there are 3,074 individuals (25,411 observations) who move across regions. Furthermore, of the 3,074 movers, 1,549 moved to a region with higher propensity to diagnose and 1,525 moved to regions with lower propensity to diagnose. In the former group 366 individuals were suffering from depression before they moved, but had not been diagnosed, and 131 of them were diagnosed after they moved. In the latter group 384 individuals suffered from depression before they moved, but had not yet been diagnosed, and 112 of them were diagnosed after they moved. Thus, 35.83% of those who moved to a region with a higher propensity to diagnose and were suffering from depression or anxiety, but had not been diagnosed, received a diagnosis after they moved. In comparison, 29.18% of those who moved to a region with a lower propensity to diagnose and were suffering from depression or anxiety, but had not been diagnosed, received a diagnosis after they moved. This provides strong evidence that our identification strategy is valid for the subsample of movers, since those who moved to regions with higher propensity to diagnose were more likely to be diagnosed.

For our IV FE to provide a causal relationship between life satisfaction and depression or anxiety both the relevance condition and the exclusion restriction must hold. To test the relevance condition, we performed a Wald test of the significance of our instrument in the first stage of the two stage least squares regression. The Chi-squared test statistic for the Wald test was 27.47 (with 1 degree of freedom, p-value < 0.001), indicating that the relevance condition holds by a significant margin. Furthermore, for the exclusion restriction to hold it must not be the case that individuals with depression or anxiety are systematically moving to areas with higher propensity to diagnose. To test this, we calculated the share of individuals suffering from depression or anxiety by region over time and the propensity to diagnose by region over time. We found that the share of individuals suffering from depression or anxiety by region is very stable over time whereas the propensity to diagnose by region is increasing over time, see Table A1 and A2, and Figures A1, and A2 in the Appendix for details. For completeness we also present the share of individuals diagnosed with depression or anxiety by region in each time period as well as the average share of individuals diagnosed by region over time, in Table A3 and Figure A3 respectively. In addition, there does not seem to be any significant relationship between the propensity to diagnose by region and the share of individuals suffering from depression or anxiety by region, see Figure A4 in the Appendix. We therefore conclude from these observations that a systematic movement of individuals with depression or anxiety to regions with higher propensity to diagnose is unlikely to be a problem in our data.

For improved CIV estimates the endogeneity of income also needs to be tackled. This is a well-known problem when estimating subjective well-being equations and a number of papers have applied instrumental-variable regressions to try to account for this (Howley, 2017; Huang et al., 2018; Powdthavee, 2010; Knight et al., 2009; Luttmer, 2005; Ólafsdóttir et al., 2020). Several instruments have been used for income including mother's education. However, even though it has been used repeatedly in the literature it is difficult to argue that it satisfies the exclusion restriction in a subjective well-being equation. Another solution used to circumvent the endogeneity of income is to substitute household income with lottery winnings and other irregular sources of income (Ambrey and Fleming, 2014; Kim & Koh, 2021; Linqvist et al., 2018). We follow this method and include windfall income instead of regular income to measure the marginal effects of increased income on life satisfaction.

When we have estimated our models, we calculate the CIV for depression or anxiety. The CIV method allows us to calculate the tradeoff between money and non-market goods, in our case mental health. The CIV is therefore the amount of money that an individual would have to receive or give up to remain at the same level of well-being following a change in mental health status. To describe the CIV method in a formal way, assume that we have the following general well-being function:

$$W(Y, MH, X). \tag{2}$$

Consider a reduction in health from MH^1 to MH^0, without changes to Y and X. A resulting change in well-being is then defined as follows:

$$\Delta W = W(Y, MH^0, X) - W(Y, MH^1, X). \tag{3}$$

The compensating income variation (CIV) is then the amount of money that equalizes the individual well-being before and after the change in health so that:

$$W(Y + CIV, MH^0, X) = W(Y, MH^1, X), \tag{4}$$

where in our case W is self-reported life satisfaction, MH is being diagnosed and suffering from depression or anxiety, and Y is windfall income. We then use the specification in equation (1) and solve for CIV in equation (4), which results in the negative ratio between the coefficients for depression or anxiety and windfall income:

$$CIV = (-\theta/\delta)wind \tag{5}$$

where *wind* denotes the mean change in income after a “major improvement in finances” in our sample. Following Au and Johnston (2015) and Johnston et al. (2017), we calculate the estimated mean change in household disposable income from a major improvement in finance (defined as reporting a “major improvement in finance” AND an increase in the household gross income). In the estimation sample, this figure is $64,413.

We calculate the CIV using all six estimation strategies. By doing this we can see where the potential biases in the CIV estimate originate from.

3 Data

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is an annual nationally representative longitudinal survey managed by the Melbourne Institute at the University of Melbourne. This dataset contains the appropriate variables required to address the research questions, with individual-level data relating to life satisfaction, measures of income, rich variables on depression, anxiety and appropriate covariates, as well as a suitable instrument for depression and anxiety. The data contains information on our key variables of interest for approximately 20,000 Australians 15 years and older, from 2001–2018. We use data from waves 2009–2018 since information on diagnoses was not collected before 2009. Over this observation period the data set contains 167,104 observations for 33,600 individuals. As previously stated, we drop 26,535 observations for 3,446 individuals, corresponding to those who are suffering from depression or anxiety but have not been diagnosed. In addition, we drop 14,327 observations for 8,758 individuals due to missing values. This results in our final sample of 126,242 observations for 21,396 individuals.

At each wave, all respondents in HILDA answer the following question about their life satisfaction: All things considered, how satisfied are you with your life? Answers vary on a scale from 0 to 10, where 0 indicates “totally dissatisfied” and 10 indicates “totally satisfied”. The scale of the life-satisfaction variable can vary between different data sets and we therefore standardize our life-satisfaction variable so that it has zero mean and variance one, so that our results can be compared to those of previous studies. Life satisfaction as a measure of subjective well-being has been extensively used to evaluate the effect of health conditions and other experiences of individuals (see e.g., Howley, 2017; Frijters et al., 2011; Powdthavee and van den Berg, 2011; Ólafsdóttir et al., 2020).

The key independent variable in our analysis is "being diagnosed and suffering from depression or anxiety", i.e. our mental health variable. To construct this variable, we need a reliable measure of individual mental health as well as information on diagnosis. For the former, we used a measure of mental health on a scale of 0-100 – one of the eight dimensions of the 36-Item Short Form Survey (SF-36) (Ware et al.,1993) – included in all waves of the HILDA data. This subscale is the SF-36 MH, which is more commonly referred to as the MHI-5. The MHI-5 scale is derived from five items, each introduced by the question "How much of the time, during the last month, have you …"

… Been a nervous person (anxiety)

… Felt so down in the dumps nothing could cheer you up (behavioural/emotional control)

… Felt calm and peaceful (general positive affect)

… Felt down (depression)

… Been a happy person (general positive affect)

Each of the five items has six answer categories ranging from "All of the Time" to "None of the Time", with summed scores thus ranging from 5-30. This score is linearly transformed to a 0-100 scale according to the standard procedure for calculation of the MHI-5 scores (Ware et al., 1993). It has been shown that the eight scales of the SF-36 data collected for the HILDA survey, including the MHI-5, are psychometrically sound, with good internal consistency, discriminant validity, and high reliability (Butterworth and Crosier, 2004). Furthermore, the MHI-5 has proven useful as a screening tool for depression and anxiety (Ware, 2000). Berwick et al. (1991) and Ware et al. (1993) showed that the optimal cut-off for detecting depression or anxiety is 52 or less, on the 0-100 scale. This has thus become the most frequently used MHI-5 cut-off point for detecting depression or anxiety (see e.g., Bültmann et al., 2006; Holmes, 1998; Rumpf et al., 2001; Strand et al., 2003; Thorsen et al., 2013). We follow that tradition and therefore use the same cut-off to determine whether a person is experiencing symptoms of depression or anxiety or not.

This indicator variable is multiplied by whether an individual has a previous diagnosis of depression or anxiety. Waves 9, 13, and 17 include a YES/NO question for having been diagnosed with depression or anxiety. Using this question, we construct a variable for each wave that is equal to one if a person has ever been diagnosed with depression or anxiety and zero otherwise. This results in our time-varying mental health variable of "being diagnosed and suffering from depression or anxiety". It is thus important to consider that since we did not only base our treatment variable on the results from the MHI-5 but also on the diagnoses of a mental-health professional we expect the treatment group to have lower life satisfaction than those who suffer from depression or anxiety but have not been diagnosed. The reason being that if a person has severe symptoms of depression or anxiety, he or she is more likely to seek help from a mental-health professional. This is empirically confirmed by comparing the average life satisfaction scores of the two groups. The average life satisfaction of those who suffer from depression and or anxiety based on the MHI-5 cutoff but have not been diagnosed is 7.39 but the life satisfaction of those who suffer from depression or anxiety and have also been diagnosed is 6.28.

The instrument for this variable is the propensity to diagnose by region and time. This variable is constructed from the ratio of those diagnosed AND suffering as a fraction of those who suffer from depression or anxiety, in each region and time period. The general release of the HILDA data includes 13 regions, which are the six states of Australia, the Northern Territory, the Australian Capital Territory, as well as five of Australia's largest cities, namely, Sydney, Melbourne, Brisbane, Adelaide, and Perth.

The windfall income variable we use is based on the question: "We now would like you to think about major events that have happened in your life over the past 12 months. For each statement state YES or NO to indicate whether each event happened in the last 12 months" – "Major improvement in financial situation (e.g., won lottery, received an inheritance)".

In addition to these key variables, we also include several controls that are likely correlated with life satisfaction. These are: Labour-force status, wave dummies, age, age squared, level of urbanization, gender, education, and number of children. Table 1 reports descriptive statistics of all variables used in our analysis.

4 Results

We find a strong effect of mental health on life satisfaction in our preferred model, and evidence across models of potential bias where no adjustments are made for endogeneity. Our results are presented in Table 2 by model specification. Table 2 is separated into panel A and B. Panel A contains the regression coefficients for being diagnosed with and suffering from depression or anxiety symptoms in the past month and windfall income, based on equation (1), and panel B contains the corresponding CIV estimates, based on equation (5).

The results from the IV FE model display highly significant effects of our two key variables on life satisfaction, namely suffering from depression or anxiety and windfall income.

The point estimate of being diagnosed and suffering from depression or anxiety is -0.077, with a standard deviation of 0.011. We use standardized life satisfaction with mean zero and variance one and therefore the estimated reduction in life satisfaction from suffering from depression or anxiety is around 7.7% of one standard deviation. Our estimate of windfall income is 0.083 with a standard deviation of 0.013. Thus, when an individual obtains $64,413 from windfall income their life satisfaction increases by 8.3% of one standard deviation.

In Panel A of Table 2, the results from our six different estimation methods show that the OLS estimates are likely to be biased upwards. Thus, not accounting for time invariant effects or the endogeneity of depression or anxiety will produce potentially misleading results. By presenting the results from all six estimations we can see where biases originate and to what extent. For example, only introducing RE or FE we obtain a coefficient which is about 50% of the OLS estimate, whereas if we use IV regression, and do not account for time invariant effects, we obtain a coefficient which is about 15% of the OLS estimate. Then by introducing either RE or FE as well as the IV we obtain an estimate which is around 6% of the OLS coefficient. From these results we see quite clearly that most of the bias in the OLS estimate originates from the endogeneity of the mental-health variable. However, by only accounting for time invariant effects using RE or FE, one can also significantly reduce the bias observed in the OLS estimate.

Panel B in Table 2 shows the CIVs calculated using the coefficients from Panel A. In line with the discussion in the previous paragraph, the CIV results further demonstrate the drastic effect of not accounting for time invariant effects and the endogeneity of the mental health variable in life-satisfaction equations. The CIV based on the OLS coefficients is $984,276 per year whereas the CIV based on the FE results is $478,538. Thus, by just allowing for FE one is able to reduce the bias of the CIV estimate by almost five hundred thousand dollars. Similarly, by only accounting for the endogeneity of mental health, using an instrumental variable regression, the CIV estimate drops down to $151,326. Then, finally by accounting for both issues at the same time, using the coefficients from the IV FE regression, we obtain a CIV estimate of $60,329 per year. The CIV results from our preferred model are therefore more than nine hundred thousand dollars lower than the estimate derived from the OLS results.

5 Discussion

We estimate the effect of suffering from depression or anxiety on life satisfaction using an instrumental-variable approach, applied to Australian panel data over the period of 2009–2018.

We exploit the exogenous variation in regional differences in propensity to diagnose depression or anxiety to construct an instrument for suffering from depression or anxiety, as well as treating the endogeneity of income by substituting income for lottery winnings or other irregular sources of income. In addition, we control for time invariant factors by including fixed effects in our main analysis. Furthermore, we use our estimates to calculate the value of not suffering from depression or anxiety using the CIV method. The results from our IV FE model and the subsequent CIV calculations are considerably lower than previous research suggests.

Previous estimates of the relationship between life satisfaction and depression and anxiety leave the endogeneity issues untreated. Two of the papers which use OLS regression to estimate the relationship between these disorders and life satisfaction include enough information for us to calculate standardized estimates, comparable to our results, namely Adams et al. (2016) and Vázques et al. (2015). The standardized depression and anxiety coefficients from Adams et al. are -1.290 and -0.009, respectively, and the same estimates from Vázques et al. are -1.132 and -0.469. In comparison, our OLS estimate of depression or anxiety is -1.360, which is much closer to the standardized depression estimates than the anxiety estimates. The likely reason for this is that more than 70% of individuals in our treatment group suffer from depression. However, we have only one wave of data with the separation of depression and anxiety, namely 2017. For this reason, it was not possible to estimate the effects of these illnesses separately.

Fergusson et al. (2015), Layard et al. (2013), and Powdthavee and van den Berg (2011) are the only papers, that we know of, that use either random or fixed effects, to estimate the relationship between mental illness and life satisfaction. Our results show that the difference between our estimates and previous research are, to a large extent, due to not adjusting for individual effects. The standardized estimation coefficient for depression or anxiety from Powdthavee and van den Berg (2011) using random effects, applied to the British household panel survey, is -0.378 compared to our random effects estimate of -0.807. The standardized estimation coefficient from Layard et al. (2013), using fixed effects, applied to the HILDA data, is -0.21 compared to our fixed effects estimate of -0.605, but we would not expect the two estimates to be the same since Layard et al. (2013) estimates the relationship between life satisfaction and suffering from any mental disorder, whereas we only include depression and anxiety. In Fergusson et al. (2015), the standardized estimation coefficients using fixed effects, applied to a birth cohort study from New Zealand, for major depression and anxiety are -0.395 and -0.219, respectively, compared to our coefficient of -0.605 for depression or anxiety. Our results are thus higher than those found in previous studies. The most likely explanation for the difference between our estimates compared to those of Powdthavee and van den Berg and Ferguson is that we only include those currently reporting depression or anxiety who have been previously diagnosed with either condition. To test this, we compared the difference between life satisfaction for those who are diagnosed and currently have symptoms versus those who have not been diagnosed but have symptoms and found that the life satisfaction of the former group is significantly lower. This suggests that this is likely to be the main factor for these differences. However, when we use IV RE and IV FE the estimated coefficients drop down to -0.104 and -0.077, respectively.

A comparison of the monetary valuation estimates for not suffering from depression or anxiety from previous research underlines the severity of the endogeneity bias even more. For example, the estimated value presented in Powdthavee and van den Berg (2011) using random-effects models is \$582,928,000 per year compared to our results of \$619,659 when we use random effects but do not instrument. The estimate from Powdthavee and van den Berg (2011) is almost thousand times higher. Similarly, the estimated value for not suffering from depression from Ásgeirsdóttir et al. (2017), is \$13,714,593 per year. Their results are based on point estimates which did not account for time invariant factors nor the endogeneity of depression or income. Our estimate based on OLS is \$984,276 per year, which is still almost \$13 million smaller than their estimate, and with the estimate based on the IV FE coefficients even lower at \$60,329 per year. To demonstrate even further that the large differences between previous estimates and our estimates is also due to income endogeneity bias, we include estimations of our model using the same six estimation strategies as before but use the logarithm of household income instead of windfall income, and thus leave the endogeneity issue untreated. The results are given in Table A4 in the Appendix and show for example that the CIV derived from the OLS estimate, where the endogeneity issue of income is not treated, is \$278,320,000.

The main policy implications of the results are the following. First, there is significant cost associated with depression and anxiety, even though it might not be as high as previously reported. Moreover, we believe that our estimates are more robust as adjustments are made to account for the endogeneity biases likely to be present in previous esimates. It is possible that the estimates can be used in cost-benefit analyses (CBA) of mental-health policy interventions. Given the fact that those estimates provide monetary value rather than QALYs, efficiency calculations are not limited to cost-effectiveness analyses (CEA). When evaluating optimal allocation of resources, policy makers can thus compare costs associated with depression and anxiety to that of goods and services in general and not just to health. Presenting those utility losses in monetary terms also reveals their size compared to other depression and anxiety-related costs. As an example, in 2017 the number of individuals in Australia age 15 and over was around 20 million (Australian Bureau of Statistics, 2017), where we see from our data that 4.83% of the population is diagnosed and currently experiencing symptoms of depression or anxiety, resulting in approximately 1 million individuals. Thus, from our CIV estimate of $60,329, the utility losses associated with depression or anxiety, for those who are diagnosed, is around $60 billion compared to the $9.9 billion spent on mental health-related services in Australia during 2017-2018 (Australian Institute of Health and Welfare, 2020). The personal costs from reduced well-being are therefore significantly higher than the expenditure on mental healthcare. However, even though there are significant costs at the individual and societal level associated with depression and anxiety, which might be higher than the costs associated with many other illnesses, it does not necessarily indicate that the policy response should be to substantially increase spending on treatment for depression and anxiety. Such a decision is also dependent on how effective treatment for these disorders is compared to that of other illnesses. An important path for future research should therefore be to produce consistent estimates of the effectiveness of treatment, in terms of improved life satisfaction.

In conclusion we find that the effect of depression and anxiety as well as the value of not suffering from depression and anxiety is likely to be overestimated in previous research. The main causes of these biased estimates are untreated endogeneity issues and any results based on models that do not account for these problems could be misleading for policy makers. We therefore encourage researchers to account for this bias in the future, for example, by using IV methods.

Declarations

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Conflicts of Interest. The authors have no conflicts of interest to declare.

Available Data and Material. The data from the HILDA survey is available to researchers.

Code availability. Codes can be made available upon request.

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Tables

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	Between	Within
Satisfaction with life (unstandardized)	8.01	1.36	1.16	0.83
Major improvement in finances %	2.84	16.61	9.16	14.7
Diagnosed and past month depression/anxiety %	5.90	23.57	19.99	14.39
Propensity to diagnose depression/anxiety %	15.35	3.46	3.32	0.98
Age	45.59	18.92	19.60	2.52
Number of children	1.66	1.56	1.56	0.29
Male %	47.66	49.95	49.97	0.00
Major cities %	65.60	47.50	45.86	14.07
Inner regions %	22.15	41.52	39.49	13.96
Outer regions %	12.25	32.79	31.74	10.70
University qualification %	24.27	42.87	40.65	10.20
Certificate or diploma %	31.12	46.30	44.36	12.42
High school or lower education %	44.55	49.70	48.16	14.65
Undetermined education %	0.06	2.47	2.52	0.41
Employed %	63.27	48.21	42.40	25.52
Unemployed %	4.09	19.81	16.77	15.78
Out of the labor force %	32.64	46.89	41.07	24.35
Number of observations				126,242
Number of individuals				21,396

Note: Between and Within refer to the between and within standard deviation of the respective variables.

Table 2: Impact of being diagnosed and suffering from depression or anxiety

Panel A Independent variables	OLS		RE		FE		IV		IV-RE		IV-FE	
Diagnosed and past month depression or anxiety	-1.360	***	-0.807	***	-0.605	***	-0.207	***	-0.104	***	-0.077	***
	(0.012)		(0.012)		(0.013)		(0.012)		(0.010)		(0.011)	
Major improvement in finances	0.089	***	0.084	***	0.081	***	0.088	***	0.085	***	0.083	***
	(0.016)		(0.012)		(0.013)		(0.017)		(0.012)		(0.013)	
Observations	126,575		126,575		126,575		126,575		126,575		126,575	
R-Squared	0.129		0.124		0.108		0.038		0.034		0.024	
Panel B	**OLS**		**RE**		**FE**		**IV**		**IV ER**		**IV FE**	
CIV	984,276	***	619,659	***	478,538	***	151,326	***	78,930	***	60,329	***
	(175,492)		(91,449)		(74,239)		(29,786)		(13,812)		(12,367)	

Note: *** p<0.01, ** p<0.05, * p<0.10. The dependent variable is standardized life satisfaction. Robust standard errors are in parenthesis. The benchmark for being diagnosed and suffering from depression/anxiety is not suffering from depression/anxiety. Control variables are age, age squared, gender, education, labor market participation, number of children, level of urbanization and year dummies. CIV estimates are given in American dollars.