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Mental health and obesity

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Abstract

Purpose – Obesity is a significant public health issue. With obesity increasing worldwide, risk factors for obesity need to be better understood and require careful examination. This study aims to examine mental health as a risk factor for obesity using longitudinal data from Australia.

Design/methodology/approach – The main identification strategy relies on the recent death of a close friend and a serious injury or illness to a family member as exogenous shocks to mental health.

Findings – The authors' preferred estimates, which account for the endogeneity of mental health, suggest that mental health has a significant negative impact on obesity. This result proves to be robust to a suite of sensitivity checks. Further investigations reveal that poor mental health leads to increased smoking, which also has an effect on obesity.

Originality/value – The study's findings provide a new perspective on how good mental health helps curb obesity.

Keywords Obesity, Mental health, Well-being, HILDA

Paper type Research paper

1. Introduction

Obesity poses significant public health problems in modern societies as well as the third world. More than 1.9 billion adults, about 40% of the world's adults, are overweight or obese (WHO, 2021). Sedentary lifestyles, with easier access to processed foods, as well as high-calorie, low-nutrient food, have contributed to this problem (Lavallee *et al.*, 2021). The

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obesity trend is alarming because excess body weight is associated with various health conditions, including heart disease, stroke, Type 2 diabetes and certain types of cancer (Blüher, 2019). The economic cost of obesity is also substantial, with excess annual medical costs in the USA of up to US$1,861 for each adult who is obese compared to people with healthy weight (Ward *et al.*, 2021).

To guide policy and help curb the obesity crisis, researchers have investigated socioeconomic factors that influence weight gain. While biological factors are well-recognised drivers of obesity, among socioeconomic factors, studies have mainly focused on the role of physical activity, dietary choices, sleep, peer effects and personality traits (Joslyn and Haider-Markel, 2019; Sa *et al.*, 2020; Fletcher, 2012; Gerlach *et al.*, 2015). However, relatively little is known about the role of mental health. Could mental health affect the incidence of obesity, and if so, what pathways could help explain this relationship?

Understanding how mental well-being influences body weight is important for economists, psychologists and policymakers. Anxiety and depression, for example, are increasingly prevalent. While about 970 million people worldwide were living with a mental health disorder in 2019, in just one year, this number rose by 26% and 28% in the prevalence of anxiety and depression, respectively (WHO, 2022a, 2022b). Mental disorders are associated with a wide range of economic and social outcomes, including mortality rates, the number of years lived with disability, schooling difficulties, lost days of work and reduced productivity (Walker *et al.*, 2015; Moussavi *et al.*, 2007; Brännlund *et al.*, 2017; Stansfeld *et al.*, 2011; Bubonya *et al.*, 2017). This study treats aspects of mental well-being and its as-yet unexamined effect on obesity.

We use panel data from the Household, Income and Labour Dynamics in Australia (HILDA) survey to investigate the effect of mental health on obesity. We further examine exercise, sleeping hours, smoking behaviour and a healthy diet as potential mechanisms through which mental health transmits to obesity. Our main identification strategy relies on the recent death of a close friend and a serious injury or illness to a family member as exogenous shocks to mental health. This follows the empirical approach proposed by Frijters *et al.* (2014) in their study of the effect of mental health on employment and other related contributions within the same field of inquiry (Yang and Zikos, 2022, 2023; Mitrou *et al.*, 2023). Although obtaining causal estimates can be a difficult empirical challenge, the identified effects can help policymakers design more targeted interventions to combat obesity.

Our study contributes to several strands of related literature, including, firstly, the factors causing obesity (Awaworyi Churchill *et al.*, 2023; Joslyn and Haider-Markel, 2019; Sa *et al.*, 2020; Fletcher, 2012; Gerlach *et al.*, 2015). While many studies have examined how physical activity, dietary habits, biological factors, the amount of sleep and personality characteristics influence obesity, relatively little is known about the role of mental health (Brumpton *et al.*, 2013; Roberts and Duong, 2016). Within this literature, two notable exceptions are Brumpton *et al.* (2013), who study the effect of anxiety and depression on the incidence of obesity among Norwegian adults, and Roberts and Duong (2016), who consider the same link among adolescents aged 11–17 years in the USA.

We add to this literature by providing new evidence about the role of mental health and by situating our study in Australia. In 2018, overweight or obese people made up two-thirds of the adult population, and as this is similar to the rate in many high-income countries, Australia offers an ideal setting to examine how mental health affects obesity [Australian Bureau of Statistics (ABS), 2018; Organisation for Economic Co-operation and Development (OECD), 2017]. Another unique aspect of our study is that we explicitly address endogeneity concerns through instrumenting for mental health.

Secondly, we contribute to the general literature on the benefits of mental well-being (Mishra and Smyth, 2014; Kesavayuth and Zikos, 2018; Kesavayuth *et al.*, 2021; O'Connor and Graham, 2019; O'Connor, 2020; Boehm *et al.*, 2012). Good mental health and well-being are associated with positive economic and social outcomes, including wages, employment, health behaviours, health-care usage and longevity. In this study, we investigate whether mental health influences a different outcome variable, obesity, and find that besides certain well-documented factors, mental health may also have important implications for obesity.

Thirdly, we contribute to the literature that examines the effect of mental well-being on physical health (Rowan *et al.*, 2005; Surtees *et al.*, 2008; Stubbs *et al.*, 2017; Kesavayuth *et al.*, 2022a; Yang and Zikos, 2022; Shangkhum and Zikos, 2023), suggesting that higher levels of mental health improve physical health. We bring nuance and perspective to the current literature by exploring the channels by which mental well-being affects a physical health disorder, obesity.

Our research shows that good mental health reduces the likelihood of being obese. This finding is robust to a suite of sensitivity checks and other extensions. Further investigations reveal that smoking behaviour is one potential channel through which mental health influences obesity.

2. Data

The HILDA survey provides the data for this study. HILDA is a nationally representative, household-based longitudinal survey that collects high-quality data on socio-demographic characteristics, labour market participation, family circumstances and health. HILDA was started in 2001 and given to 14,000 people in 7,682 households. Data on body weight were consistently collected from 2006 onwards, so our sample covers the period 2006–2020. Our sample includes individuals over the age of 20 years who gave information on all relevant variables in each survey wave. These sample selection criteria led to an unbalanced panel of 174,711 observations from 20,453 unique individuals.

2.1 Obesity

We measure obesity using self-reported weight and height. According to the World Health Organisation, a person is "overweight" if they have a BMI between 25 and 29.9. A BMI above 30 identifies the person as obese (WHO, 2020). Accordingly, we construct a dummy variable that takes the value 1 if the respondent's BMI score is 30 kg/m^2 or more, and 0 otherwise. To determine BMI, a person's weight in kilograms is divided by their height in meters squared. A higher BMI therefore indicates a greater health risk.

We also examine the effects of obesity classes and the severity of obesity. A BMI score of 30.0–34.9 is considered Class I obesity, a BMI score of 35.0–39.9 is Class II, while a BMI score above 40 is Class III. A BMI less than 30 indicates that the respondent is not obese. The different obesity classes allow us to determine if the effects of mental well-being on obesity are heterogeneous.

As shown in the Appendix in Table A1, about one-quarter of the respondents in our sample are obese. In addition, the prevalence of obesity increased by about 9 percentage points – from 22.4% in 2006 to about 31.5% in 2020. These figures are consistent with the national averages for Australia (AIHW, 2022).

2.2 Mental health

Our main mental health variable uses 14 items from the 36-item Short Form Health Survey (SF-36). These items can be grouped into four scales: social functioning, role-emotional, mental health and vitality. The HILDA survey provides the scores for each of the four scales of mental health, in which 0 is the lowest and 100 is the highest. The Cronbach's alpha reliability statistic is around 0.83, affirming the reliability of the four scales. Consistent with existing studies, the four mental health scales are averaged for each observation (Zhu, 2016; Kesavayuth *et al.*, 2020; Yang and Zikos, 2022) [1].

In a robustness check, the Mental Health Inventory (MHI-5), consisting of five items, provides an additional measure of mental well-being. Researchers in the social sciences, including economists, often use the MHI-5 scale (Buddelmeyer and Powdthavee, 2016; Awaworyi Churchill *et al.*, 2020), which serves as a reasonable proxy for mental well-being (Hemingway *et al.*, 1997; Yamazaki *et al.*, 2005) [2]. To help interpret the results, we standardised these measures of mental health, with a mean of 0 and 1 as the standard deviation.

2.3 Mechanisms

We use HILDA data on physical activity, smoking behaviour, eating habits and the amount of sleep [3]. The frequency of physical activity comes from asking: "In general, how often do you participate in moderate or intensive physical activity for at least 30 min?" Answers are reported on a six-point scale ranging from 0 (not at all) to 5 (every day).

Information about smoking behaviour is taken from responses to a question about cigarette smoking or other use of tobacco products. Choice of responses include 0 (I have never smoked or I no longer smoke), 1 (I smoke less often than weekly), 2 (I smoke at least weekly but not daily) and 3 (I smoke daily). In addition, survey participants were to indicate the number of hours they sleep per week, which we use to investigate sleep as a potential channel.

Information on eating behaviour is drawn from responses to four statements asking whether or not the respondent:

(1) eats fruits every day;

(2) eats vegetables everyday;

(3) avoids (meaning, eats less than once per month) foods high in fat like French fries, hot chips or wedges; and

(4) drinks skim or low-fat milk.

Following Cobb-Clark *et al.* (2014) and Kesavayuth *et al.* (2023), an approximation of the Healthy Eating Index was created as a sum of the "yes" responses to the questions above. The score can range from 0 to 4 and is rescaled to be between 0 and 1 to help interpret the results as moving from no eating habits to many (Cobb-Clark *et al.*, 2014). For ease of reading, we further standardised according to how often the respondent exercises, how often they smoke and the hours of sleep they get, so that the mean is 0 and the standard deviation is 1.

2.4 Control variables

In line with other studies, we control for a standard set of socio-economic and demographic attributes likely to influence obesity (Avsar *et al.*, 2017; Sa *et al.*, 2020; Joslyn and Haider-Markel, 2019; Awaworyi Churchill *et al.*, 2023). These include age, gender, BMI at baseline, household size, number of resident children, real household income, marital status, pregnancy in the past year, employment status, number of friends, educational attainment, life satisfaction and whether the individual reports having a long-term health condition or disability. We also control for geographic regions to capture time-invariant differences across Australian states and for time (waves) to account for time trends in obesity that people have in common.

Food price variation can significantly impact households' ability to afford, for example, a diet of fruit and vegetables (Cobiac *et al.*, 2017). To account for this possibility, we further control for the food Consumer Price Index (CPI), which is available from the Australian Bureau of Statistics by state and year. In a robustness check, we also include the Big Five personality traits as additional control variables, given that obesity may correlate with given psychological traits (Bagnjuk *et al.*, 2019).

2.5 Descriptive statistics and a first glance at the data

Table A1 presents descriptive statistics for the whole sample and is also broken down for individuals above (index > 0) and below (index ≤ 0) the average on the standardised mental health index. On average, 26% of the respondents are obese. We also observe that BMI and obesity rates are lower for those who have better mental health relative to those with worse than average mental health. The difference in the prevalence of obesity is about 9 percentage points, which is statistically significant at the 1% level. Further, those with higher mental well-being are more likely to be married, educated and satisfied with their lives. They are less likely to have a long-term health condition, and report having many friends, more children and higher income.

3. Methodology

To determine the role mental health plays in obesity, we use this regression model:

$$Obesity_{it} = a_i + \beta MH_{it} + X_{it}'\gamma + \mu_s + \tau_t + \varepsilon_{it} \quad (1)$$

where $Obesity_{it}$ is a dummy variable indicating whether the BMI score of individual i is more than 30 at time t, indicating obesity; MH_{it}, our explanatory variable of interest, represents the individual's mental health; X_{it} is a vector of standard socio-economic and demographic characteristics; α_i captures individual-level fixed effects; μ_s and τ_t are dummy variables representing state and wave fixed effects; and ε_{it} is the error term.

Our baseline results are based on ordinary least squares (OLS) and fixed effects (FE) regressions [4]. However, these estimates will be biased if mental health is endogenous. Endogeneity may arise from omitted variables, such as genetics, family history of mental health problems and childhood circumstances, that could be correlated with mental health and obesity. Endogeneity may also emerge from reverse causality, given that people who are obese tend to do less outside the home, less physical activity with fewer travel and leisure activities, all of which are important markers of mental health. Additionally, the mental health measure is only an imperfect proxy of a person's mental health; thus, measurement error could confound our estimates.

We adopt an instrumental variables procedure controlling for fixed effects for each individual (FE-IV) to overcome these potential issues. The recent death of a close friend is the chosen instrument. The HILDA survey requests the following: "We now would like you to think about major events that have happened in your life over the past 12 months". One choice is "Death of a close friend". Using these responses, a dummy variable that equals 1 is created if the death of a close friend happened within the previous year. The death of a friend as an instrument for mental health is supported by the literature examining the effect of mental health on employment (Frijters *et al.*, 2014), physical health (Yang and Zikos, 2022) and health behaviours (Yang and Zikos, 2023; Mitrou *et al.*, 2023).

To be valid, our instrument must satisfy two assumptions. Firstly, it must correlate with mental health. Brown *et al.* (1993) and Kessler (1997), among others, show that the death of a friend and other experiences of loss are detrimental to mental health. Figure A1 confirms the validity of this measure. In the distribution of the standardised mental health index, the left-hand tail indicates lower mental health levels for those with a close friend who died.

Secondly, the instrument must satisfy the exclusion restriction; it must be uncorrelated with obesity, except through mental health. This assumption is reasonable, as loss events are typically randomly distributed across the sample. In other words, our instrument – the death of a close friend – is unlikely to impact obesity directly, except through the channel of decreased mental health. Given that instrument validity can only be tested in over-identified cases, we use an additional instrument based on the list of adverse life events included in HILDA. The instrument is constructed as a dummy variable that takes the value 1 if the respondent reported a serious injury or illness to a family member in the past year [5].

There may however be other pathways through which the instruments influence the incidence of obesity, which lessens the validity of the exclusion restriction. For instance, a friend's death, or the serious injury or illness of a family member, may affect one's life values or attitudes, marking a turning point in a person's health-related behaviour, which would affect whether they are obese or not. One way to deal with this issue is to ask whether the subject has a more positive view/perspective of life. Accordingly, the regression models were adjusted for life satisfaction, a well-attested and reliable measure (Pavot and Diener, 1993). Life satisfaction is measured on an 11-point scale, from 0 (totally dissatisfied) to 10 (totally satisfied). Including this additional control helps generate more precise estimates of the causal effect of interest.

4. Main results

4.1 Baseline results

Baseline estimates for the correlation of mental health to obesity are shown in Table 1. If a person has greater mental well-being, he or she is less likely to be obese. In Column 1, a standard deviation increase in mental health correlates with a 1.1 percentage point decline in the likelihood of being obese, while in Column 2, a standard deviation increase in mental health is associated with a decrease of 0.7 percentage points in the likelihood of being obese. The estimates are highly significant at the 1% level.

The results for the other covariates are consistent with expectations. We find that, on average, obesity is more prevalent in women than men. Obesity is positively associated with BMI at baseline and age and negatively associated with education or more resident children. Being married and being out of the labour force increase the prevalence of obesity. By contrast, a higher food CPI and having many friends lessen the likelihood of obesity. Greater life satisfaction and pregnancy in the past year tend to increase the incidence of obesity.

However, the finding that better mental health reduces the probability that the person is obese cannot be taken at face value. There is the possibility of reverse causality, that obesity is driving the poor mental health, rather than mental health causing the obesity. Therefore, endogeneity-corrected estimates are presented in the next section.

4.2 Results corrected for endogeneity

Table 2 presents IV estimates, which use as instruments a friend's death and a family member's serious injury or illness in the previous year. Table 2 at the bottom shows first-stage results, indicating that the F-statistic is greater than 10, and that the instruments are relevant (Stock and Yogo, 2005). The Hansen J-statistic, which equals 0.197, is not statistically significant; thus, we cannot reject the null hypothesis that the overidentifying

	OLS	FE
Mental health	–0.011*** (0.001)	–0.007*** (0.001)
BMI baseline	0.055*** (0.000)	
Age	0.005*** (0.000)	0.016*** (0.002)
Age squared	–0.000*** (0.000)	–0.000*** (0.000)
Female	0.051*** (0.002)	
Having many friends	–0.005*** (0.000)	–0.002*** (0.001)
Real household income	–0.000*** (0.000)	0.000 (0.000)
Unemployed	0.009* (0.005)	–0.006 (0.004)
Not in the labour force	0.008*** (0.002)	0.007*** (0.002)
Years of education	–0.006*** (0.000)	–0.002** (0.001)
Number of resident children	–0.008*** (0.001)	–0.006*** (0.002)
Household size	0.004*** (0.001)	0.002 (0.001)
Married	–0.001 (0.003)	0.031*** (0.005)
De facto	–0.003 (0.003)	0.025*** (0.004)
Separated	–0.008 (0.005)	–0.004 (0.007)
Divorced	0.008** (0.004)	0.005 (0.007)
Widowed	0.012** (0.005)	0.002 (0.008)
Being pregnant last year	0.022*** (0.003)	0.027*** (0.003)
Long-term health condition	0.023*** (0.002)	0.001 (0.002)
Life satisfaction	0.001** (0.001)	0.001* (0.001)
Food category CPI	–0.014*** (0.000)	0.002 (0.001)
Observations	174,711	174,711
Number of individuals	20,453	20,453

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Standard errors are in parentheses. The models include a set of dummy variables for survey waves and Australian regions of residence
Source: Created by authors

Table 1. Mental health and obesity (baseline estimates)

restrictions are valid. The first-stage results show that the passing of a close friend, or a family member's serious injury or illness results in lower mental well-being, which is consistent with expectations.

After correcting for endogeneity, it is clear that the effect of mental well-being on obesity remains negative to a statistically significant degree. Specifically, a standard deviation increase in mental health brings about a decline in the probability of being obese by 4.2 percentage points. While appearing to be small, the magnitude of this point estimate does not imply a negligible effect on obesity. Suppose we compare the estimated size of the effect (–0.042) with a different significant life event, such as being married. In that case, we find that the latter accounts for about 74% of the effect of mental well-being on obesity, *ceteris paribus*. Mental health generally has a larger effect on obesity than education, unemployment or being pregnant, suggesting that the effect is economically meaningful.

While the IV estimates in Table 2 are consistent with the baseline estimates in Table 1, the IV results are considerably larger. This means that endogeneity generally has a downward bias, which is not surprising in the OLS and FE results. Although widely used and validated in previous studies, our index of mental well-being is still an imperfect proxy of a person's true mental health and, thus, is likely to suffer from measurement error. If the reason for the measurement error is classical, this may cause attenuation bias that could help explain the smaller estimates observed in the OLS and FE results.

To examine the robustness of the FE-IV results, we also present estimates using an alternative IV method based on the control function procedure (Heckman and Robb, 1985; Wooldridge, 2015). Using this method, we initially regress mental health on the included

Table 2.
Mental health and obesity (FE-IV estimates)

	Obesity
Mental health	–0.042** (0.022)
Age	0.016*** (0.002)
Age squared	–0.000*** (0.000)
Having many friends	0.000 (0.001)
Real household income	0.000 (0.000)
Unemployed	–0.007* (0.004)
Not in the labour force	0.003 (0.003)
Years of education	–0.002** (0.001)
Number of resident children	–0.007*** (0.002)
Household size	0.002 (0.001)
Married	0.031*** (0.005)
De facto	0.026*** (0.004)
Separated	–0.006 (0.007)
Divorced	0.005 (0.007)
Widowed	–0.001 (0.009)
Being pregnant last year	0.026*** (0.003)
Long-term health condition	–0.007 (0.005)
Life satisfaction	0.007* (0.004)
Food category CPI	0.002 (0.001)
Observations	174,711
Number of individuals	20,453
First stage (DV: mental health)	
Death of friend	–0.022***
Injury or illness to family member	–0.081***
F-statistic	145.13
Hansen *J*-statistic	0.197
p-value	0.6575

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Standard errors are in parentheses. The model includes a set of dummy variables for survey waves and Australian regions of residence. DV means dependent variable
Source: Created by authors

exogenous variables and the two excluded instruments. We obtain the first-stage residuals and, without replacing the endogenous mental health variable, control for those residuals in the second-stage estimating equation. This procedure allows us to account for the effects of unmeasured or unobserved confounders as an alternative method of IV estimation (Guo and Small, 2016). Table 3 displays the results, which are in line with the FE-IV and baseline estimates, showing that better mental health decreases the probability of obesity.

Table 3.
Mental health and obesity (control function method)

	Obesity
Mental health	–0.042** (0.021)
Residuals	0.035 (0.021)
Observations	174,711
Number of individuals	20,453

Notes: **$p < 0.05$. Standard errors are in parentheses. The model includes the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence
Source: Created by authors

4.3 Channel analysis

We also consider the importance of physical activity, smoking behaviour, eating habits and the amount of sleep as potential pathways through which mental health could influence obesity (e.g. Baron and Kenny, 1986; McKinnon *et al.*, 2007; Tran and Zikos, 2019; Kesavayuth *et al.*, 2022b; Awaworyi Churchill *et al.*, 2023). As a first step, we examine the effects of mental health on the potential pathways. The results in Table 4 show that a standard deviation increase in mental health reduces smoking frequency by 0.173 standard deviations. This is consistent with the finding that a greater sense of well-being, including mental health, tends to encourage healthier behaviours (e.g. Boehm *et al.*, 2012; Yang and Zikos, 2023; Mitrou *et al.*, 2023).

In Table 5, as a second step, we report estimates from a regression that includes smoking behaviour as an additional covariate. Panel B shows re-estimated baseline results without any mediators, while Panel A reports estimates that also control for smoking behaviour. We find that smoking reduces obesity. A standard deviation increase in smoking frequency is associated with a 2 percentage point decline in the likelihood that a person is obese. This result ties in with earlier findings that smoking is a metabolic stimulant that tends to suppress appetite (e.g. Courtemanche *et al.*, 2018).

After adding smoking behaviour as a control variable, the total effect of mental health on obesity can be decomposed into a direct and an indirect effect. Our analysis, reported in Panel A of Table 5, reveals that the direct effect of mental health is –0.046. The indirect effect, calculated as the product of two coefficients from Tables 4 and 5 (–0.173 and –0.02), amounts to 0.0034. The total effect, which is the sum of the direct and indirect effects, equals –0.042. These results suggest that smoking behaviour is a potential channel through which mental health influences obesity.

5. Robustness checks and extensions

In this section, we examine the sensitivity of our results to various robustness checks and extensions. The mental health variable was constructed using 14 items from the SF-36 for our main results. We also consider the five-item MHI-5, a subscale of the SF-36, which is collected with: "How much of the time during the past four weeks:

(1) Have you been a very nervous person;

(2) Have you felt so down in the dumps that nothing could cheer you up;

	Physical activity	Smoking frequency	Eating habit	Sleeping hours
Mental health	–0.032 (0.066)	–0.173*** (0.045)	–0.157 (0.096)	–0.195 (0.498)
Observations	174,466	173,889	35,297	19,850
Number of individuals	20,437	20,422	12,086	9,925
First stage (DV: mental health)				
Death of friend	–0.022***	–0.022***	–0.026*	–0.019
Injury or illness to family member	–0.080***	–0.081***	–0.056***	–0.039**
F-statistic	165.752	167.33	2.015	2.88
Hansen *J*-statistic	1.483	3.037	2.015	0.53
p-value	0.223	0.081	0.156	0.463

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Standard errors are in parentheses. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence. DV means dependent variable
Source: Created by authors

Table 4. Effects of mental health on mediators (FE-IV estimates)

	Obesity
Panel A – result for mechanism	
Mental health	–0.046** (0.022)
Smoking frequency	–0.020*** (0.001)
Observations	173,889
Number of individuals	20,422
First stage (DV: mental health)	
Death of friend	–0.022***
Injury or illness to family member	–0.081***
F-statistic	166.6
Hansen *J*-statistic	0.321
p-value	0.571
Panel B – baseline result for comparison	
Mental health	–0.042** (0.021)
Observations	173,889
Number of individuals	20,422
First stage (DV: mental health)	
Death of friend	–0.022***
Injury or illness to family member	–0.081***
F-statistic	167.332
Hansen *J*-statistic	0.244
p-value	0.621

Notes: ***$p < 0.01$; **$p < 0.05$. Standard errors are in parentheses. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence. DV means dependent variable
Source: Created by authors

Table 5. Effect of mediator on obesity (FE-IV estimates)

(3) Have you felt calm and peaceful;
(4) Have you felt downhearted and blue; and
(5) Have you been a happy person?".

Potential responses range from 1 (none of the time) to 6 (all the time). HILDA provides the overall score for the MHI-5 scale from 0 to 100, with a higher value indicating better mental health. As shown in Panel A of Table A2, improved mental well-being reduces the odds of being obese to a statistically significant degree, confirming our findings.

Next, we include additional controls to determine how robust the results of the study are. Previous research suggests that excess body weight can be linked with the Big Five personality traits: agreeableness, conscientiousness, extraversion, neuroticism and openness to experiences (e.g. Bagnjuk *et al.*, 2019; Gerlach *et al.*, 2015). To shed some light on this issue, we use HILDA data on the Big Five, available in Waves 5, 9, 13 and 17. These waves do not overlap with the waves used in our main analysis. Thus, for each trait, we calculate the average score over the available data period and include that as an additional control. The results, reported in Panel B of Table A2, show that our main findings are not sensitive to including the Big Five.

The instruments used here were measured using the past 12 months as the reference period. However, for some people, the impact of death events or other adverse life experiences may last a relatively short time. It could be argued that the instruments would be more precisely defined if the reference period was shorter than a year. To further check how robust the results are, we use the past six months as the reference period in defining our instruments. Panel C of Table A2 shows mentally healthy people as less likely to be obese, confirming our main findings.

For our mediation analysis, we use a linear model to estimate the effect of mental health on smoking, given it is easier to interpret than an ordered logit model. Because smoking behaviour is a categorical variable that ranges from 0 (I have never smoked or I no longer smoke) to 3 (I smoke daily), we conduct two further checks to examine if our results are sensitive to the linearity assumption. Firstly, we set a dummy variable equal to 1 if the respondent is a current smoker and 0 otherwise. Secondly, instead of using a dummy, we consider the frequency of smoking as an outcome variable. Table A3 displays the results. Column 1 reports results from a logit regression, while Column 2 reports results from an ordered logit regression. We find evidence of a negative relationship between mental health and smoking behaviour, in line with our main findings.

Next, we consider the heterogeneous effects of mental health on obesity across population subgroups [6]. Firstly, we investigate the mental health effects of those who are overweight and those in the different obesity classes. As the data section explains, we consider three obesity classes corresponding to BMI scores: 30.0–34.9, 35.0–39.9 and 40 or higher. A BMI less than 30 indicates that the respondent is not obese: those with a BMI score of 18.5–24.9 are classified as having normal weight, while a BMI score of 25.0–29.9 identifies someone as overweight.

Table A4 displays the results, which show that greater mental well-being increases the chances of being overweight. This finding could be linked with the argument that greater mental well-being promotes social capital (Lyubomirsky *et al.*, 2005). Those with high mental well-being may feel more comfortable attending social gatherings or going out to eat with friends, which can contribute to weight gain. By contrast, greater mental well-being lowers the chance that a person will be in the different obesity classes. The estimated effect is relatively stronger for individuals with Class 1 obesity than those in the other obesity classes. This is consistent with the idea that those with Class 1 obesity may have more favourable hormonal profiles and slightly higher metabolic rates (e.g. Singla *et al.*, 2010; Poddar *et al.*, 2017), making the incidence of obesity more responsive to changes in mental well-being.

Overall, we find that greater mental well-being may increase the chance of being overweight while reducing the chance of being in any of the obesity classes. Several studies document that a greater sense of well-being encourages healthier behaviours (Boehm *et al.*, 2012; Yang and Zikos, 2023; Mitrou *et al.*, 2023). Our results bring more nuance to the literature, suggesting that the positive association between mental well-being and healthier behaviours holds for some but certainly not all groups of individuals when it comes to the incidence of overweight and obesity.

This study also investigates the impact of mental health on obesity by gender. A large body of literature confirms an existing gender gap in obesity. In most countries, the prevalence of obesity in adults appears to be greater among women than men (Cooper *et al.*, 2021; Garawi *et al.*, 2014). To test for possible gender differences, we report separate estimates for men and women. The results in Table A5 show that the coefficient on mental health continues to be negative and significant, in line with our previous findings. The effect of mental health seems to be relatively stronger for women than men. Nonetheless, using a test of equal coefficients, we find that at the 95% confidence level, there is no systematic difference between men and women in how mental well-being influences obesity.

In a final set of checks, we investigate the heterogeneous effects of mental health across age groups and gender. Firstly, we examine the effects of mental health on respondents who are young (20 to 44 years), middle-aged (45 to 65 years) and old (66 to 85 years). Secondly, we conduct a subsample analysis on those respondents aged up to 50 years and those aged 51–85. We further differentiate the last two age groups by gender to examine if there is a differential impact on obesity due to the onset of menopause for women after the age of 50.

Tables A6 and A7 display the results. Table A6 suggests that better mental health is negatively associated with the chance that someone is obese. This result holds true only among young and middle-aged individuals. We also find that the effect of mental health on obesity is equally strong for these two age groups.

Table A7 shows that mental well-being is statistically significant among younger men and women but not their older counterparts. Greater mental well-being is associated with a lower likelihood of being obese only for those aged up to 50. Further, the estimated effects are not uniform: mental well-being has a greater impact on younger women than men. To test for possible differences in the estimates, we use a two-sample z-test. At the 95% confidence level, we find that there is no appreciable difference between younger women and men as to the effect of mental health on obesity. These results also indicate that the incidence of menopause does not seem to play any role in how mental health relates to obesity.

6. Conclusion

Obesity is a serious public health problem with significant social and economic costs. Obesity is on the rise throughout the world, so its causes should be investigated. This paper examined the role played by mental well-being on this question, using 15 waves of nationally representative longitudinal data for Australia. We found that good mental health reduces the likelihood that one is obese. An increase of one standard deviation in mental well-being reduces the chance of being obese by 4.2 percentage points, an effect size that is also important from an economic perspective. This general conclusion holds to several sensitivity checks.

We also examined whether physical activity, smoking behaviour, eating habits and the amount of sleep are channels through which mental health could influence obesity. We found that the relationship between mental health and obesity is mediated by smoking behaviour. Individuals who have lower levels of mental health tend to smoke more frequently, and this is associated with a decline in their likelihood of being obese. The negative effect of smoking on obesity may indicate either that there are more smokers and non-obese people who were already obese before starting to smoke, or that people who want to lose weight because they are obese tend to smoke to suppress the desire to eat.

Shortcomings of this study include the fact that our estimates represent a local average treatment effect, meaning, we capture the effect of mental health on obesity for the so-called compliers. These are subjects who have been affected, with respect to their mental health, by the recent passing of a close friend or by a serious injury/illness to a family member. This implies that the estimated mental health effect may differ from the effect that would be derived had we used some other factor for identification.

Another possible limitation is that the results reported in our study are specific to Australia. Although obesity rates in Australia are similar to those in many high-income countries (ABS, 2018; OECD, 2017), our estimates may not apply to other countries, especially developing ones. Nevertheless, researchers should find the estimation approach used here helpful in extending the analysis to other environments and institutional settings. Examining the potential disparities between developed and developing nations, for instance, holds promise as a fruitful avenue for understanding the vital role that mental well-being plays with respect to obesity.

Our findings are important as economists are becoming increasingly interested in reducing the prevalence of obesity. Given that mental health has a significant part to play in the incidence of obesity, policymakers might consider supporting those with, for example, anxiety or depression. Policies geared to combat obesity could provide additional funding treating and preventing mental illness. Thus, in addition to the well-established factors that may help to reduce the incidence of obesity, our findings show that the promotion of mental well-being could be another effective way to curb the obesity crisis.

Notes

1. Qualitatively similar conclusions can also be reached using the predicted factor obtained from factor analysis, which relaxes the assumption of equal weights in the mental health index. The estimates are available from the authors on request.
2. This sensitivity check, along with a discussion of the MHI-5 scale, are included in Section 5.
3. The variable capturing the amount of sleep is available only in Waves 13 and 17 of the HILDA survey, while data on a person's diet is available in Waves 7, 9, 13 and 17. Information on physical activity and smoking behaviour is available over the entire sample period from 2006–2020.
4. We also used a logit model as part of robustness checks to ensure our results were not sensitive to the estimation method, reaching qualitatively similar conclusions. The estimates are available upon request.
5. For this life event too, we observe a similar empirical pattern to that depicted in Figure A1.
6. Given that the FE-IV estimates are consistent with FE and OLS estimates, we rely on FE models for the heterogeneity analysis. This allows us to circumvent the problem of maintaining sufficiently large estimation sample sizes that would otherwise be essential for identification within a FE-IV model (Frijters *et al.*, 2014).

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Appendix

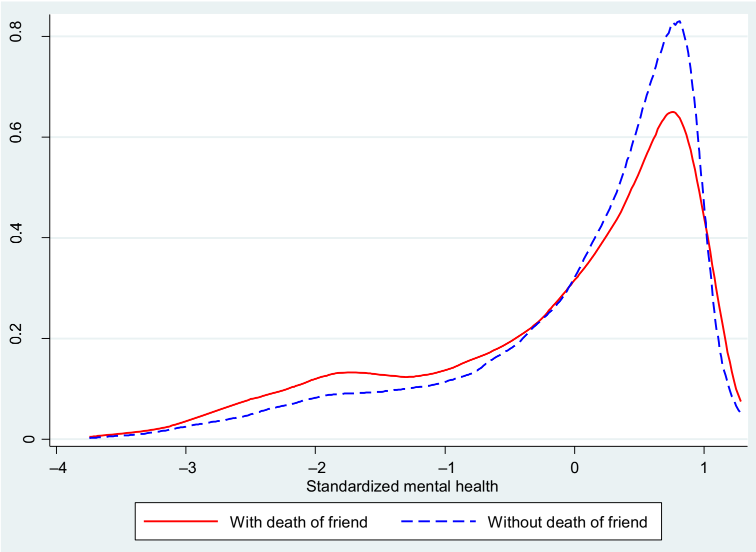

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Figure A1.
Kernel density estimates of the standardized mental health index

Table A1.
Sample means of outcomes and key covariates by mental health level

	All respondents	Below average (index ≤ 0)	Above average (index > 0)
BMI	27.19	27.938	26.775***
BMI baseline	26.45	27.062	26.108***
Obesity	0.26	0.315	0.224***
Age	47.11	47.706	46.789***
Female	0.53	0.580	0.499***
Household size	2.78	2.686	2.829***
Number of resident children	0.77	0.727	0.789***
Real household income	88.95	76.910	95.546***
Having many friends	14.03	2.907	3.655***
Years of education	14.03	13.764	14.172***
Married	0.54	0.469	0.579***
De facto	0.16	0.161	0.165**
Separated	0.03	0.039	0.022***
Divorced	0.07	0.088	0.054***
Widowed	0.04	0.050	0.033***
Never married and not de facto	0.16	0.192	0.147***
Employed	0.67	0.562	0.727***
Unemployed	0.03	0.040	0.022***
Not in the labour force	0.30	0.397	0.251***
Death of friend	0.11	0.130	0.099***
Injury or illness to family member	0.15	0.187	0.127***
Being pregnant last year	0.06	0.056	0.060***
Long-term health condition	0.28	0.472	0.178***
Life satisfaction	7.91	7.232	8.284***
Food category CPI	102.37	102.814	102.129***
Sample size	174,711	61,871	112,840

Notes: Figures are sample means or proportions. *** and ** denote, respectively, 0.01 and 0.05 significance levels for two-group mean comparison *t*-test, relative to the group with below-average mental health
Source: Created by authors

	Obesity
Panel A – alternative mental health measure	
Mental health component (MHI-5)	–0.047** (0.024)
Observations	174,711
Number of individuals	20,453
First stage (DV: MHI-5)	
Death of friend	–0.027***
Injury or illness to family member	–0.072***
F-statistic	139.38
Hansen *J*-statistic	0.09
p-value	0.7637
Panel B – controlling for the Big Five traits	
Mental health	–0.040** (0.018)
Extraversion	–0.002 (0.002)
Agreeableness	–0.000 (0.002)
Conscientiousness	–0.008*** (0.003)
Emotional stability	0.007* (0.004)
Openness	0.001 (0.002)
Observations	169,339
Number of individuals	18,430
First stage (DV: mental health)	
Death of friend	–0.035***
Injury or illness to family member	–0.090***
F-statistic	226.92
Hansen *J*-statistic	0.951
p-value	0.3294
Panel C – shortening the reference period for the IVs	
Mental health	–0.032* (0.019)
Observations	174,711
Number of individuals	20,453
First stage (DV: mental health)	
Death of friend during the past 6 months	–0.017***
Injury or illness to family member during the past 6 months	–0.070***
F-statistic	82.46
Hansen *J*-statistic	2.436
p-value	0.1186

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Standard errors are in parentheses. The regression models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence. DV means dependent variable. Figures in Panels A and C are estimated coefficients from FE-IV models, while figures in Panel B are estimated coefficients from a random-effects instrumental variables model
Source: Created by authors

Table A2. Mental health and obesity (robustness checks)

Table A3.
Effect of mental health on smoking (non-linear estimates)

	(1) DV is smoking probability	(2) DV is smoking frequency
Mental health	–0.117*** (–0.020)	–0.153*** (–0.018)
Observations	38,265	173,920
Number of individuals	4,125	20,453

Notes: ***p < 0.01. Standard errors are in parentheses. In Column (1), the dependent variable is the probability of being a current smoker. In Column (2), the dependent variable is smoking frequency. Column (1) reports estimates from a fixed-effects logit regression, while Column (2) reports results from a random-effects ordered logit regression. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence. DV means dependent variable
Source: Created by authors

Table A4.
Mental health and obesity classes

	Overweight	Obesity class 1	Obesity class 2	Obesity class 3
Mental health	0.004** (0.002)	–0.007*** (0.001)	–0.004*** (0.001)	–0.005*** (0.000)
Observations	126,765	155,891	166,195	171,554
Number of individuals	17,692	19,654	20,153	20,347

Notes: ***p < 0.01, **p < 0.05. Standard errors are in parentheses. Figures are estimated coefficients from linear FE models. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence
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Table A5.
Mental health and obesity by gender

	Females	Males
Mental health	–0.008*** (0.001)	–0.006*** (0.002)
Observations	92,188	82,523
Number of individuals	10,667	9,786

Notes: ***p < 0.01. Standard errors are in parentheses. Figures are estimated coefficients from linear FE models. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence
Source: Created by authors

Table A6. Mental health and obesity by age groups

	(1) 20–44 years old	(2) 45–65 years old	(3) 66–85 years old
Mental health	–0.009*** (0.001)	–0.010*** (0.002)	0.001 (0.002)
Observations	81,081	64,954	28,676
Number of individuals	12,640	9,216	4,555

Notes: ***p < 0.01. Standard errors are in parentheses. Figures are estimated coefficients from linear FE models. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence
Source: Created by authors

Table A7. Mental health and obesity by gender and age groups

	Females		Males	
	(1) 20–50 years old	(2) 51–85 years old	(3) 20–50 years old	(4) 51–85 years old
Mental health	–0.012*** (0.002)	–0.002 (0.002)	–0.008*** (0.002)	–0.001 (0.002)
Observations	53,537	38,651	47,675	34,848
Number of individuals	7,575	4,885	7,042	4,364

Notes: ***p < 0.01. Standard errors are in parentheses. Figures are estimated coefficients from linear FE models. The models include the usual covariates in Table 2, as well as a set of dummy variables for survey waves and Australian regions of residence
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