AN ECONOMIC EXPLORATION OF OBESITY, QUALITY OF LIFE AND CONSUMER PREFERENCES

by

JODY CHURCH

Centre for Health Economics Research and Evaluation
UTS Business School

UNIVERSITY OF TECHNOLOGY SYDNEY

Submitted in total fulfilment of the requirements of the degree of Doctor of Philosophy

2019

CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not been previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information and literature used are indicated in the thesis.

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Jody Church

22 February 2019

ACKNOWLEDGMENTS

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS – formerly the Department of Families, Housing, Community Services and Indigenous Affairs) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute. I would like to acknowledge the financial support I received from UTS throughout my candidature. Professional editing of the draft thesis was provided by Matthew Sidebotham in accordance with the university-endorsed Guidelines for Editing Research Theses.

I am grateful to my supervisor, Professor Stephen Goodall, for his unwavering support and guidance throughout my PhD candidature. I would not have finished without his invaluable feedback and encouragement that keeping me motivated and helping pull me out of my Stata ‘rabbit holes’. His understanding and patience were most appreciated as I tried to juggle two babies and a PhD. I would also like to thank Professor Marion Haas, my other supervisor, for her continuing support, keen eye for detail and remarkable feedback; and Associate Professor Kees van Gool for stepping in and providing helpful econometric advice and for his sage advice in the final throes of my thesis: ‘This is the best I could do with the time that I had’.

A special thanks to Dr. Bonny Parkinson for her friendship since I started at CHERE, for being an amazing sounding board, someone I could always rely on to keep me motivated and share her wealth of knowledge. Similar thanks to Liz Chinchen for her friendship since starting at CHERE and her motherly concern for both me and my family. The help with the literature searches and referencing was much appreciated. and Sheena for a kind ear and best person to share an office with. Professor Debbie Street, for helping me with the design of the DCE and bestowing her knowledge (which was too intelligent for me to grasp at times!)

A huge thanks to Kathleen Manipis for keeping the final year of my PhD fun and exciting, giving me the motivation to continue, and helping me wrangle in the literature search. Who knew obesity was such a huge topic! Dr. Phil Haywood, for not only providing invaluable guidance throughout my PhD but also helping me navigate through some health issues and Brendan Mulhern, for allowing me to badger him with DCE questions. Thanks to Sopany Saing and Elena Meshcheriakova for their friendship and motivation, and Vanessa for her patience and helping me get through all the administration that comes with PhDs, work contracts and babies.

A big thank you to everyone at CHERE, not only for the support throughout my PhD, but also through milestones such as marriage, and the birth of my son and daughter, which all happened during my candidature. Furthermore, for their patience and understanding as I cared for my son and daughter during my maternity leave (and the many sick leave days). Of course, to all my friends who have been supportive over the years with lots of laughter and special memories. To Jess Bilbe, for her help navigating motherhood and for being an amazing person. And to Monica Brockmyre, a kind soul, who has been my rock over the years. Thank you!

I am eternally grateful to my Mom and Dad for their motivation for academic achievement from very early days, for flying out from Canada to help give me time to focus on writing my thesis, and their endless love and support as I decided to make a career out of being a 'student'. To my sister, who has always had my best interests at heart and an unwavering belief in me. And my in-laws, who helped out even when they should have been relaxing on vacation.

Finally, and most importantly, I would like to thank my family, Steve, Evan and Gabrielle. To Steve, my husband, for supporting me on this journey and being understanding when stressful moments took hold and when writing became my priority. You are my rock and I love and appreciate everything you do for our family. And to Evan and Gabrielle who both came into my life during the PhD journey and provided me with endless smiles (and distractions) and ultimately provided my 'raison d'être'.

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ABSTRACT

This thesis explores aspects of obesity using economic methods. Specifically, the research provides insight into the issues of conducting economic evaluations of obesity interventions, the relationship between quality of life (QoL) and weight change, and consumer preferences for weight loss programs and future health benefits.

The thesis comprises five studies. The first reviews current economic evaluations of interventions to reduce obesity. This study demonstrates that claims of cost-effectiveness are often overstated, with inadequate documentation and questionable modelling. In particular, the modelling approaches inherently assume that individuals gain QoL when weight is lost, even though this has not been demonstrated.

The next two studies examine the relationship between obesity and QoL using a national panel data set of 19,914 individuals – the Household Income and Labour Dynamics Australia (HILDA) survey. The cross-sectional analysis supports previous research findings that obese individuals have a lower QoL relative to normal weight individuals. However, the longitudinal analysis demonstrates that reductions in body weight do not correspond to short-term improvements in QoL. Instrumental variable analysis suggests that the impacts on QoL may be mediated through poorer mental health that persists after weight loss.

In the fourth study, a discrete choice experiment was developed to elicit preferences between two hypothetical weight-loss programs. An online panel was used to recruit over 1,800 respondents, representative of the Australian population. Respondents preferred lower-cost individually-tailored exercise programs. Surprisingly, programs that led to an improvement in QoL were highly significant, relative to weight-loss alone. This result reinforces the need for a greater focus on QoL outcomes. Preferences were generally similar across weight groups.

The final study explores the idea that obese individuals may have different rates of time preference. A multiple staircase approach was used across four different scenarios; the results did not support the theory that obese individuals are more present-focused. However, the results did suggest that obese individuals may discount health and money differently.

Overall, the social and economic burden of obesity is a major public health concern and developing interventions and assessing their outcomes is important in addressing the current obesity epidemic. The results from this thesis demonstrate that there is an important association between obesity and QoL. However, the trade-offs for individuals who are overweight or obese are complex and multifaceted.

GLOSSARY

Abbreviation	Description
ABDS	Australian Burden of Disease Study
ABS	Australian Bureau of Statistics
AIC	Akaike information criterion
AHS	Australian Health Survey
AIHW	Australian Institute of Health and Welfare
AUD	Australian dollar
BIC	Bayesian information criteria
BMI	Body Mass Index (kg/m^2)
CEA	Cost-effectiveness analysis
CHERE	Centre for Health Economics Research and Evaluation
CI	Confidence interval
COI	Cost of illness
CUA	Cost–utility analysis
DALY	Disability Adjusted Life Year
DCE	Discrete Choice Experiment
EQ-5D	European Quality of Life (EUROQoL) 5 Dimensions
GMNL	Generalised multinomial logit
HILDA	Household Income and Labour Dynamics in Australia Survey
ICER	Incremental Cost-Effectiveness Ratio
IIA	Independence of irrelevant alternatives
iid	Independent and identically distributed
MNL	Multi-nominal logit
MXL	Mixed logit
mWTP	Marginal willingness to pay
NHS	National Health Survey
NHS	National Health Service (UK)
NR	Not reported
NSW	New South Wales
OECD	Organisation for Economic Co-operation and Development

OLS	Ordinary least squares
OOP	Out of pocket
PBAC	Pharmaceutical Benefits Advisory Committee
PBS	Pharmaceutical Benefits Scheme
QALY	Quality Adjusted Life Year
QoL	Quality of Life
RCT	Randomised controlled trial
RP	Revealed Preferences
RUT	Random Utility Theory
SE	Standard error
SF-36	Short Form 36
SF-6D	Short Form 6 Dimensions
SG	Standard Gamble
SP	Stated Preferences
TTO	Time trade-off
WHO	World Health Organization
WTP	Willingness to pay

‘It is very injurious to health to take in more food than the constitution will bear, when, at the same time one uses no exercise to carry off this excess.’

— *Hippocrates*

1 INTRODUCTION

1.1 Background

Rates of overweight and obesity are increasing worldwide. The World Health Organization (WHO) estimates that rates have nearly tripled since 1975, with more than 1.9 billion adults currently overweight and 650 million of these obese (World Health Organization (WHO), 2018). In Australia, rates of overweight and obesity have steadily increased over the past 30 years (National Health and Medical Research Council (NHMRC), 2015). It is estimated that two in every three Australian adults and one in every four Australian children are overweight or obese (Australian Institute of Health and Welfare (AIHW), 2016a). High body mass is considered one of the biggest contributors to a population's burden of disease, together with tobacco use, physical inactivity, high alcohol use and high blood pressure (AIHW, 2016a). Governments are under pressure to reduce rates of obesity due to the associated comorbidity and mortality, as well as the economic burden associated with the condition.

Obesity has now become a major health challenge and population-level approaches to prevent excess weight are imperative (Australian Medical Association (AMA), 2016). The Global Burden of Disease Study 2013 states that 'urgent global action and leadership is required to assist countries to more effectively intervene' (Ng et al., 2014). Remarkably, there is limited evidence of public health measures that have been successful in producing a sustained reduction in the prevalence of obesity (Swinburn et al., 2011). Public health measures have proven difficult to implement as these policies need to influence behaviours around lifestyles at the individual level (Chan & Woo, 2010).

1.2 Definition of Overweight and Obesity

The WHO defines overweight and obesity as 'abnormal or excessive fat accumulation that may impair health' (WHO, 2018). The most commonly used criterion to classify obesity and overweight is Body Mass Index (BMI), a measure of weight-to-height ratio that is consistent across both sexes and all ages of adults. BMI is the most suitable measure of overweight and obesity at a population level, as it is easy to collect via self-report questionnaires, since most people know their height and weight, and it allows for comparisons within and between populations. It can also be used to identify individuals at an increased risk of morbidity and mortality.

BMI is defined as a person's weight in kilograms divided by the square of height in metres (kg/m^2). Based on the WHO classification, a BMI of 18.5–25 is considered normal weight, a BMI greater than or equal to 25 overweight and a BMI greater than or equal to 30 obese. Individuals with a BMI greater than 35 are classified as severely obese and those with a BMI greater than 40 are classified as morbidly obese. Table 1.1 summarises the BMI classifications, as well as the risk of comorbidities for each of the weight categories.

Table 1.1 BMI classifications

BMI (kg/m^2)	WHO classification	Risk of comorbidities
<18.5	Underweight	Low (other problems increased)
18.5–24.99	Normal weight	Average
25–29.99	Overweight	Mildly increased
30–34.99	Obese (Class I)	Moderate
35–39.99	Severely obese (Class II)	Severe
≥ 40	Morbidly obese (Class III)	Very severe

Source: Table 2. 1 'Classification of adults according to BMI'. World Health Organization (WHO), 2000.

BMI is strongly correlated with body fat percentage but cannot distinguish between the heavier weight of lean muscle mass and body fat. Therefore, it may not be appropriate for particular body shapes (such as a muscular builds) (Nuttall, 2015) or particular ethnicities (for example the Asian population[1]) (Wellens et al., 1996; Lin et al., 2011; International Obesity Taskforce WHO, 2000).

1.3 The prevalence of obesity

The prevalence of overweight and obesity has been increasing worldwide, with 'at least one-third of the world's adult population either overweight or obese' (Seidell & Halberstadt, 2015). Since 1980, the prevalence of obesity has doubled in over 70 countries, with an estimated 603.7 (CI: 592.9–615.6) million obese adults worldwide (GBD Obesity Collaborators, 2017). This translates to 12% of adults globally being considered obese. Globally, it is estimated that excess body weight was responsible for approximately four million deaths and a loss of 120 million disability-adjusted life years in 2015 (GBD Obesity Collaborators, 2017).

The Organisation for Economic Co-operation and Development (OECD)[2] has estimated that in 2015, 19.5% of the populations in OECD countries were obese and predicts that obesity rates

[1] The proposed classifications for adult Asians by BMI are: normal weight (18.5-22.9), overweight (23-24.9), obese (25-29.9) and severely obese (≥ 3000)

[2] The OECD countries include: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Mexico,

will rise steadily until at least 2030 (OECD, 2017). The rates of overweight and obesity vary considerably across OECD countries, from 3.7% in Japan to 38.2% in the United States (Figure 1.1). Out of the 35 OECD countries, Australia has one of the highest prevalence of obesity, behind only the United States, Mexico, New Zealand and Hungary.

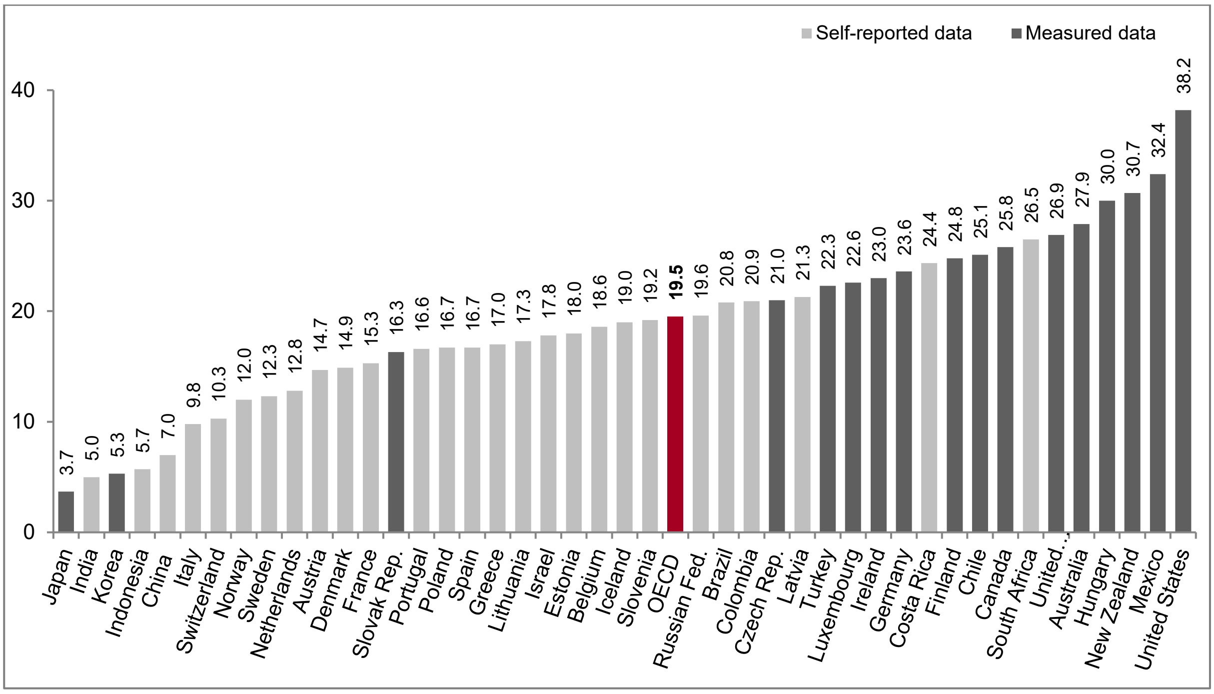


Figure 1.1 Obesity among adults, 2015 (or nearest year)
Source: OECD update, 2017.

The 2014–15 Australian National Health Survey[3] estimated that 63.4% of Australians were overweight or obese. In the adult population, 35.5% (6.3 million) are overweight and 27.9% (4.9 million) are obese, meaning that approximately 11.2 million Australian adults are considered overweight or obese. The proportion of Australians by BMI weight category is presented in Figure 1.2. In 2014–15, 71% of men and 56% of women were overweight or obese. The main difference between males and females is that men are more likely to be classified as overweight (42% compared to 29%). Both genders have similar rates of obesity (28% and 27% respectively).

Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States.

[3] Australian Bureau of Statistics (2015), National Health Survey: First Results, 2014–15, Table 8.1 Body Mass Index, waist circumference, height and weight(a)(b), Persons (estimate), cat. No. 4364.0.55.001. Retrieved on 27 October 2017, <http://www.abs.gov.au/ausstats/abs@.nsf/mf/4364.0.55.001>

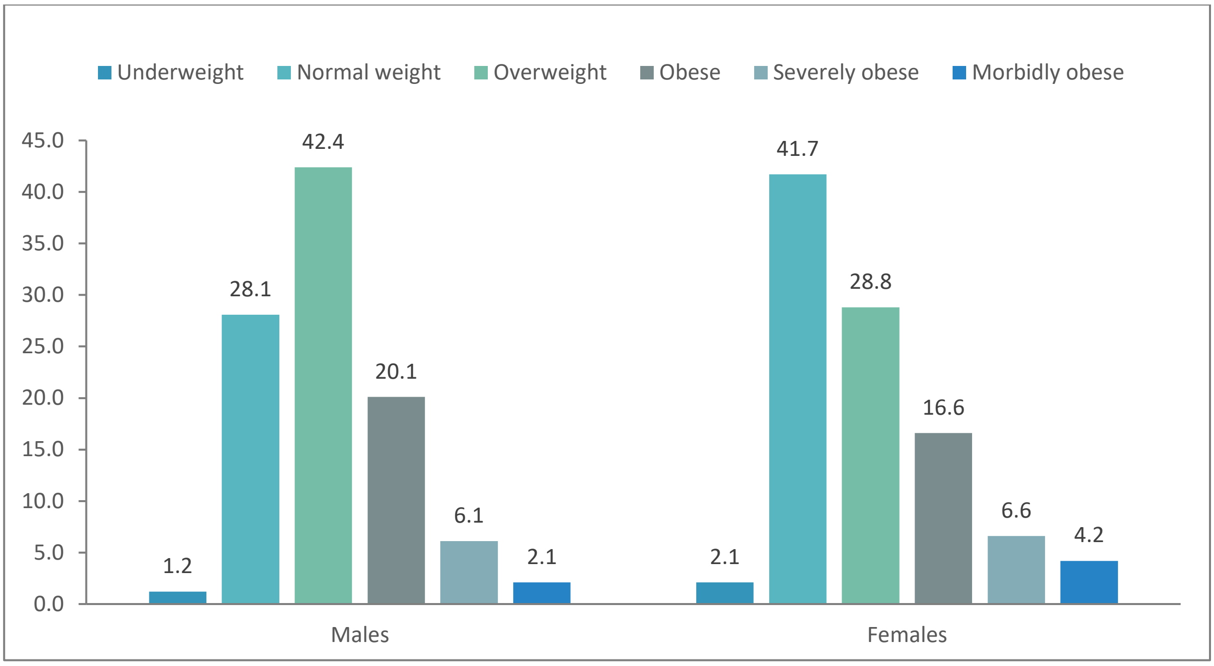


Figure 1.2 Body Mass Index by gender (2014–15)
Source: 2014–15 Australian National Health Survey.

BMI tends to increase with age, with the youngest cohorts having the lowest rate of obesity and the highest proportion of normal weight individuals (Figure 1.3). The AIHW reports that Indigenous Australians, particularly those who live outside major cities and in lower socioeconomic groups, have a greater likelihood of being obese (AIHW, 2017b). A further breakdown of overweight and obesity status by gender and age can be found in Appendix 1.

1.4 Causes of obesity

The cause of weight gain is uncontroversial; we gain weight when the calories consumed are greater than calories expended. Therefore, from a biological context, the rise in obesity can be attributed to either an increase in calories consumed, a reduction in calories expended or a combination of both (Hill et al., 2012). However, understandings of the causes of the recent trend in obesity are contentious and policy recommendations to address it are unclear.

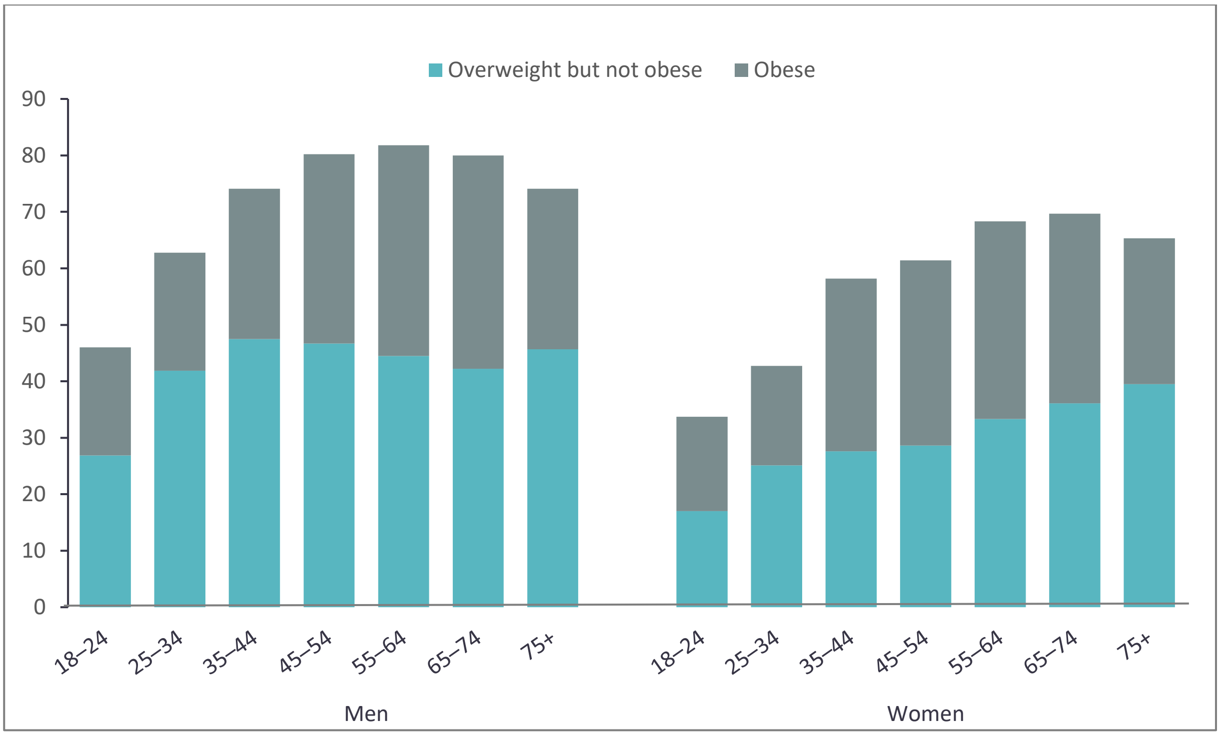


Figure 1.3 Proportion of overweight and obese adults by age group (2014–15)
Source: 2014–15 Australian National Health Survey.

Evidence suggests that it is an increase in energy intake rather than decreased energy expenditure that explains the increase in weight at a population level (Swinburn et al., 2009; Cutler et al., 2003; Craig et al., 2004; Bleich et al., 2008). This finding is supported by studies that analysed physical activity changes and concluded that decreased physical activity is unlikely to have fuelled the obesity epidemic (Westerterp & Speakman, 2008). The scientific evidence suggests that a diet with too many calories and/or a diet with high levels of sugar and fat (as opposed to a lack of physical activity) is the main cause of obesity (Jakicic et al., 2003; Ledikwe et al., 2005). However, agreement about this is not universal. A study using data from Australia, the USA and Europe has reported that both physical activity and energy intake have contributed to the obesity epidemic (Stubbs & Lee, 2004). Another international study of obesity in developed countries found that increases in caloric intake – mostly through technological advances and changing sociodemographics – are to blame for the rise in obesity (Bleich et al., 2008).

1.4.1 Economic causes of obesity

From an economic perspective, the increase in obesity worldwide can be partly attributed to changes in the global food system (Swinburn et al., 2011). The food supply has become more processed, resulting in more affordable and easily accessible food choices. It has been proposed that sociodemographic changes, such as increased urbanisation and higher numbers of women in the labour force, have also been a factor in increased caloric intake (Bleich et al., 2008). Technological change has led to a reduction in the number and type of jobs requiring physical activity and lowered the cost of preparing foods with time-saving devices (Lakdawalla & Philipson, 2009; Borghans & Golsteyn, 2006).

Public health policies commonly focus on only two of the factors that cause increased obesity rates, reduced physical activity and food manufacturing/marketing practises, described as 'the Big Two' explanations (Keith et al., 2006). However, the focus on these two causes may exclude other relevant factors that deserve attention. Other potential causes include decreased sleep, reduced rates of smoking, increased use of pharmaceuticals, changes in the distribution of ethnicities and age groups, intrauterine and intergenerational effects and possibly obesity-predisposing genotypes.

As mentioned, there are numerous economic causes of obesity, including food prices, working mothers, urbanisation, technological change and an increase in the rate of time preferences[4] (Rosin, 2008; Baum & Chou, 2011; Courtemanche et al., 2015; Lakdawalla & Philipson, 2009). However, many studies report contradictory findings (Cawley, 2015) or only focus on one cause at a time (Craig et al., 2004). A recent review of how economic factors have influenced the rise in obesity rates in the USA found little evidence that state-level economic factors (unemployment rate, alcohol prices, petrol prices, fast food prices, groceries relative to nongrocery item prices, healthier foods relative to less-healthy food prices, number of restaurants, internet access) have impacted obesity rates (Finkelstein et al., 2012). These results are similar to those reported by Baum and Chou (2011), who found that economic variables account for only a small part in the rise of obesity, with the decline in cigarette smoking the most significant contributor (Baum & Chou, 2011). Conversely, a study by Courtemanche et al. (2015) suggests that economic factors explain 37%, 43% and 59% of the rise in BMI, obesity and class II/III obesity respectively, with the increase in the number of restaurants and large-scale grocery stores having the greatest impact (Courtemanche et al., 2015).

Health agencies such as the National Health Service (NHS) in the UK, have focused on so-called 'obesogenic environments', those that encourage the consumption of unhealthy food and

[4] Time preferences refers to trade-offs between costs and benefits that occur at different points in time.

discourage exercise, as an important cause of obesity. An obesogenic environment represents 'the role environmental factors may play in determining both nutrition and physical activity' (Jones et al., 2007). This includes socioeconomic status as well as the social and physical environment (Lipek et al., 2015). One example is that public places (such as stations, theatres, shopping centres) are increasingly in close proximity to or incorporate food shops selling high-calorie foods such as burgers, pastries, sweets etc. It has been argued that many of the determinants of obesity lie outside the health sector (Garrard, 2009), which in turn shifts the blame from an individual's behaviour to policymakers. Figure 1.4 describes the obesogenic environment and the multiple influences on obesity.

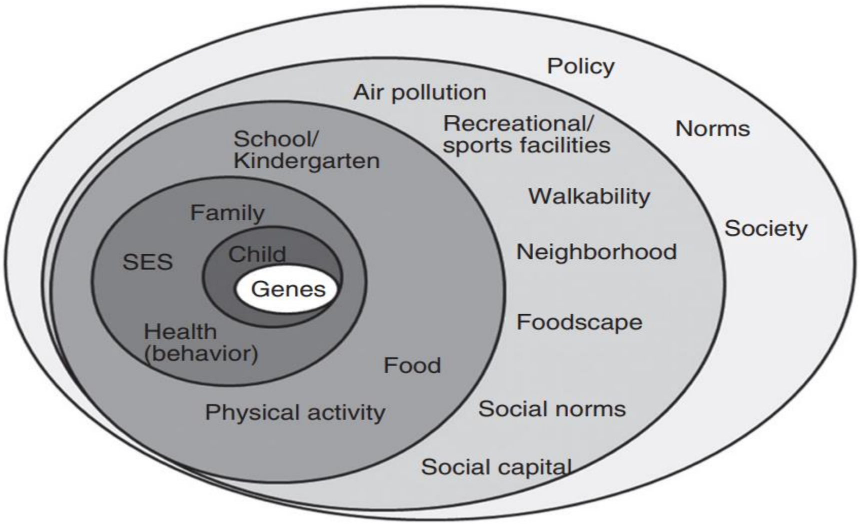


Figure 1.4 Obesogenic environment
Source: Lipek et al., 2015.

1.5 Health consequences of obesity

The increase in obesity rates has serious implications for health outcomes given the associated mortality and morbidity. The five major health risks of obesity are chronic diseases, cardiovascular disease (CVD)/stroke, cancer, metabolic/endocrine diseases and psychosocial diseases. An overview of all the health risks associated with overweight and obesity is provided in Table 1.2.

Table 1.2 Health risks associated with overweight and obesity

Body system	Health risk
Cardiovascular	Stroke Coronary heart disease Cardiac failure Hypertension
Endocrine	Type 2 diabetes Polycystic ovary syndrome
Gastrointestinal	Non-alcoholic fatty liver disease Gallbladder disease Pancreatic disease Gastro-oesophageal reflux disease Cancers of the bowel, oesophagus, gall bladder and pancreas
Genitourinary	Chronic kidney disease – glomerulopathy, end-stage renal disease Kidney cancer Kidney stones Prostate cancer Stress urinary incontinence (women) Sexual dysfunction (men)
Pulmonary	Obstructive sleep apnoea Obesity hypoventilation syndrome Asthma
Musculoskeletal	Osteoarthritis – especially the knees Spinal disc disorders Lower back pain Disorders of soft tissue structures such as tendons, fascia and cartilage Foot pain Mobility disability (particularly in older adults)
Reproductive health	Menstrual disorders Miscarriage and poor pregnancy outcome Infertility/sub-fertility Breast cancer (postmenopausal women) Endometrial cancer Ovarian cancer
Mental health	Depression Eating disorders – binge eating disorder Reduced health – related quality of life

Source: Grima and Dixon, 2013.

Overweight and obesity is the second-highest contributor to the burden of disease in Australia, after tobacco smoking (AIHW, 2016b). Excess body fat causes metabolic changes in the body that increase the risk of many health conditions, including cardiovascular disease, Type 2 diabetes and some cancers (Harvard T.H. Chan School of Public Health, 2018; McGee, 2005; Guh et al., 2009). Increased body mass predisposes individuals to many site-specific cancers, with excess weight contributing to an estimated '41% of uterine and 10% or more of gallbladder, kidney, liver, and colon cancers' (Bhaskaran et al., 2014). Likewise, obesity impacts an individual's quality of life (QoL) and is a contributor to clinical depression, anxiety and other mental health disorders (Kasen et al., 2007; Luppino et al., 2010; Roberts et al., 2003; Kim & Kawachi, 2008).

The Australian Diabetes, Obesity and Lifestyle study (AusDiab), a national longitudinal population-based study, determined that, compared to normal weight individuals, those classified as overweight were 26 times more at risk of developing obesity (Tanamas et al., 2013). Additionally, the prevalence of depression was 80% higher in those who were obese compared to those with a normal BMI.

High body mass[5] together with physical inactivity, high blood pressure and tobacco/alcohol use caused the highest burden of disease in 2011 (Australian Institute of Health and Welfare, 2016b). The Australian Burden of Disease Study (ABDS) estimated that overweight and obesity caused 7% of the total disease burden in Australia in 2011. The overall burden was somewhat higher in males than females (7.3% and 6.6%) and in older age groups (84% between the ages of 45 and 84) (AIHW, 2017a). Most of the burden of disease from overweight and obesity is attributable to diabetes, osteoarthritis, stroke, coronary heart disease and breast cancer in women (Figure 1.5).

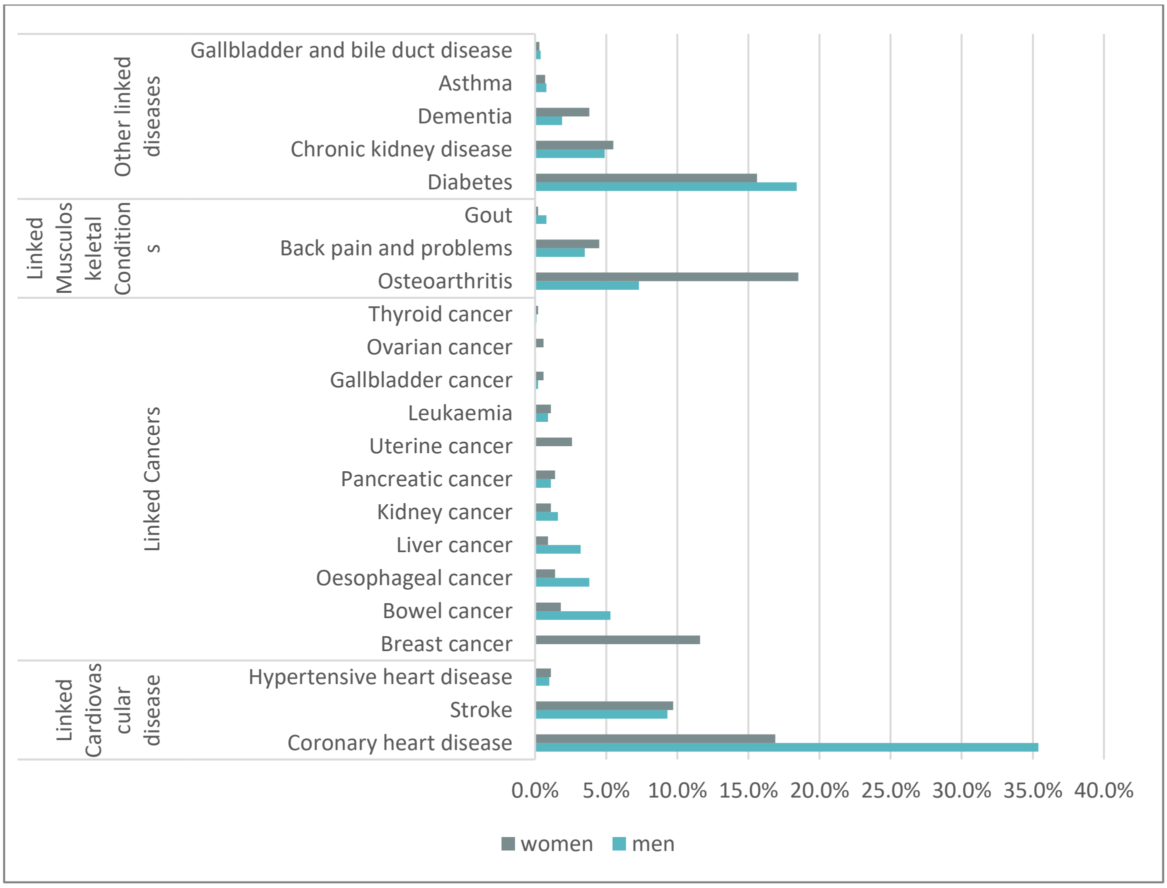


Figure 1.5 Burden of disease attributable to overweight and obesity in Australia, 2011
Source: Table 3.2, Australian Institute of Health and Welfare, 2017a.

[5] The report does not specific whether high body mass means ‘obese’ or ‘overweight and obese’

Burden of disease can be expressed as disability-adjusted life years (DALY), a measure that combines life years lost (premature death) with years lived in ill health or disability. It is estimated that high body mass is responsible for 245,816 DALYs lost (5.5% of the total disease burden in Australia) (AIHW, 2016b). Other risk factors that can be attributed to obesity, such as physical inactivity and diet, create additional overall disease burden. Table 1.3 displays the total burden of disease in Australia by risk factors.

Table 1.3 Total burden of leading risk factors of disease, 2011

Risk factor	Deaths		DALY	
	Number	Per cent	Number	Per cent
Tobacco use	18,762	12.8	402,377	9.0
High body mass	11,564	7.9	245,816	5.5
Alcohol use	6,570	4.5	227,666	5.1
Physical inactivity	11,489	7.8	224,198	5.0
Blood pressure	14,570	9.9	221,315	4.9
High blood plasma glucose	5,356	3.7	121,880	2.7
High cholesterol	5,174	3.5	106,151	2.4
Occupational exposures and hazards	1,536	1.0	88,393	2.0
Drug use	1,926	1.3	78,943	1.8
All dietary risks (joint effect) [(a)]	17,771	12.1	322,763	7.2
All risk factors (joint effect) [(a)]	64,992	44.3	1,414,978	31.5

Source: Australian Burden of Disease Study: Impact and causes of illness and death in Australia, 2011. Excel supplementary table, Chapter 6: Table S6.2 (AIHW, 2016b).

1.6 Economic consequences of obesity

In addition to the health risks and disease burden associated with high body mass, there are substantial societal and economic costs. The most recent report by PricewaterhouseCoopers (PwC) estimated that the per annum cost of obesity in Australia was $8.6 billion[6] in 2011–12 (PwC, 2015). This study used a 'bottom-up approach' and estimated the total direct and indirect costs of obesity to society to be $3.8 billion and $4.8 billion dollars respectively (in 2014–15 dollars) (PwC, 2015). Direct costs include all medical care costs (GPs, specialists), allied health, hospital care, pharmaceuticals and weight-loss interventions. The indirect cost estimates include poorer labour outcomes (lower wages and low rates of employment) and increased absenteeism, productivity losses and early retirement. Some cost estimates also include broader societal costs, including premature death, loss of QoL and carer costs (Figure 1.6).

[6] This value has been inflated to 2014–15 dollars to allow comparison with earlier studies.

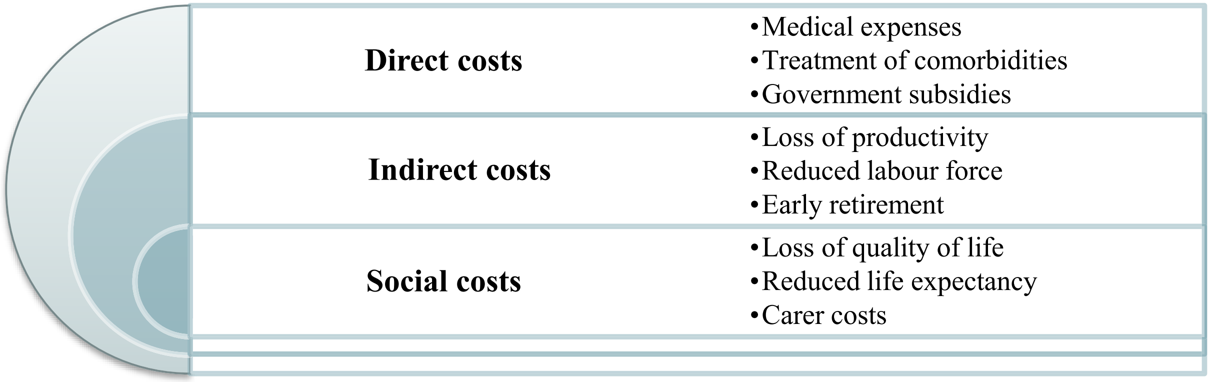


Figure 1.6 The costs of obesity

There have been a number of other studies investigating the cost of obesity in Australia (Table 1.4). In general, there is agreement that the total combined direct and indirect costs of obesity range from $8.6 to $9.7 billion per annum. These studies are comparable in their costing estimates; overall they differ in terms of the estimated contribution of direct and indirect costs.

Table 1.4 Per annum costs of obesity

	Direct Costs	Indirect costs	Social costs
PwC Study 2015	$3.8 billion	$4.8 billion	
Colagiuri 2010	$7.7 billion[a]	$2.0 billion	$15.9 billion[b]
Access Economics 2008	$5.5 billion	$4.2 billion	$58.2 billion
Medibank 2010	$1.5 billion	$7.3 billion	$42.7 billion

Note: all figures are calculated in A$2014–15 dollars. [a]Based only on BMI and excludes overweight. [b]Estimated cost of government subsidies (Naughton, 2016).

Colagiuri et al. (2010), estimated that the total indirect and direct costs of obesity are $9.7 billion per annum (Colagiuri et al., 2010). If the costs of overweight individuals are included, the total per annum cost of overweight and obesity in 2014–15 dollars is estimated at $21.9 billion ($12.3 billion for overweight and $9.7 billion for obese individuals). The authors also estimated that an additional $37.7 billion per annum was spent in government subsidies for overweight and obese people, including aged pensions, disability pensions, veteran pensions, mobility allowances and unemployment benefits.

The Access Economics report estimated that the total cost of obesity, including the net cost of lost well-being, was $67.9 billion dollars in 2005. This was higher than reported by Medibank Health solutions (a private health insurer), which estimated a total cost of $51.5 billion based on an assessment of the cost savings from reduced prevalence of obesity.

A recently published systematic review (which included Australian studies) reported that overweight and obese individuals have higher health care costs for most health care services, with costs increasing as the severity of obesity increases (Kent et al., 2017). The cost estimates presented in (Colagiuri et al., 2010) similarly showed that increasing obesity is associated with higher costs. Based on BMI measurement, the total annual direct costs of health service use per person in 2005 was $1,710 ($1,464–$1,956) for normal weight, compared to $2,110 ($1,887–$2,334) for overweight and $2,540 ($2,275–$2,805) for obese individuals (Colagiuri et al., 2010). A further analysis calculated the annual costs by weight change from 1999–2000 to 2004–05 (Figure 1.7).

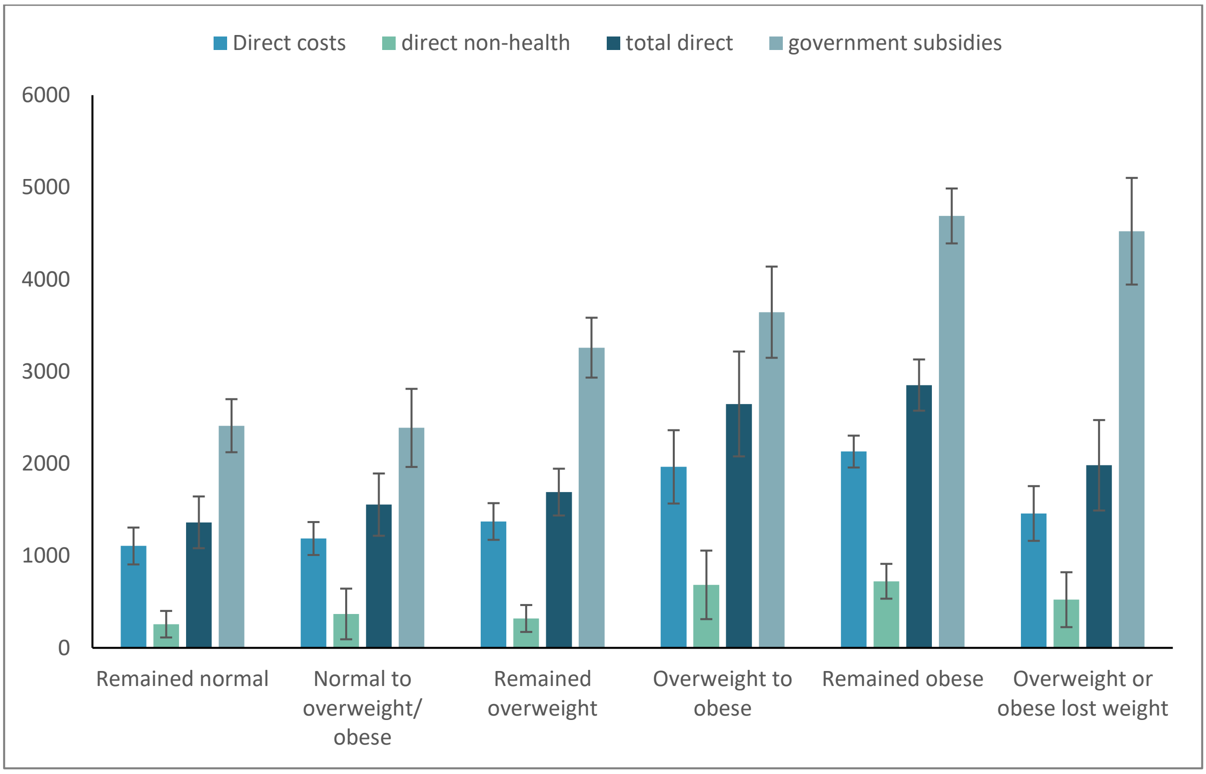


Figure 1.7 Annual costs by weight change (1999–00 to 2004–05)
Source: Box 2 estimates (Colagiuri et al., 2010).

Most of the costs are incurred by individuals who become obese, or remain obese, either as direct and indirect costs or through government subsidies. These results demonstrate that costs increase with greater severity of obesity. This poses a significant issue as, in Australia, there is a shortage of specialist services to treat clinically severe obesity (≥35 BMI) (Atlantis et al., 2018). Due to the multiple health conditions caused by obesity, specialists are needed in addition to general practitioners. However, due to the shortage of services, patients face long wait times, high out-of-pocket expenses and lack of access in rural areas.

The literature suggests that excess weight has a negative effect on labour market outcomes, however the direct cause has not been established. There is evidence of reduced employment opportunities for obese individuals due to the stigma associated with being obese (Puhl & Heuer 2010). Perceived traits that people often attribute to obese individuals - such as laziness, lack of willpower or lower levels of social skills - can cause prejudice and discrimination against obese persons in the labour market (Averett, 2014). A large body of literature has found that a wage penalty exists for overweight women, although there are mixed results for men (Baum & Ford, 2004; Cawley, 2004; Han et al., 2009). It has been suggested that a lower wage rate for obese individuals may be due to their tendency to discount future benefits at a higher rate, indicated by overeating, and a lower tendency to invest in enhancing their wage potential (Zhang & Rashad; 2008; Cawley, 2004). It is possible that there is an underlying trait that affects both lower productivity and the likelihood of being obese, but the evidence is lacking on this causal link (Gottler et al., 2017).

An Australian study did not find any effect of BMI on wages, but a significant wage premium for taller males and females (Kortt & Leigh, 2010). These findings reinforce those reported by Lee (2014), which showed no significant association between BMI and wages but suggested that being both tall and slim drives the wage premium (Lee, 2017).

It is apparent that, regardless of the methodology to estimate the costs of overweight and obesity, high body mass is a costly burden financially and socially (Lee, 2017). The PwC report estimates that if nothing is done to reduce the obesity rates in Australia, by 2025 we can expect the societal cost of obesity to be $87.7 billion per annum (PwC, 2015).

1.7 Projections for the future

It has been estimated that if current weight trends persist, over 70% of Australians will be overweight or obese by 2025 (Walls et al., 2012; Obesity Australia, 2014). Simulations of the Australian population over 30 years were run on a nationally representative cohort from 1995, resulting in an estimated 35% of the population being obese and a further 13% severely obese by 2025 (Hayes et al., 2017). The results indicate a corresponding decline in healthy weight/underweight groups, with approximately 20% of males and 30% of females considered healthy or underweight by 2025 (Figure 1.8). Comparable results were reported in a study from 2012 that predicted 83% of males and 75% of females over the age of 20 would be overweight or obese by 2025 (Haby et al., 2012).

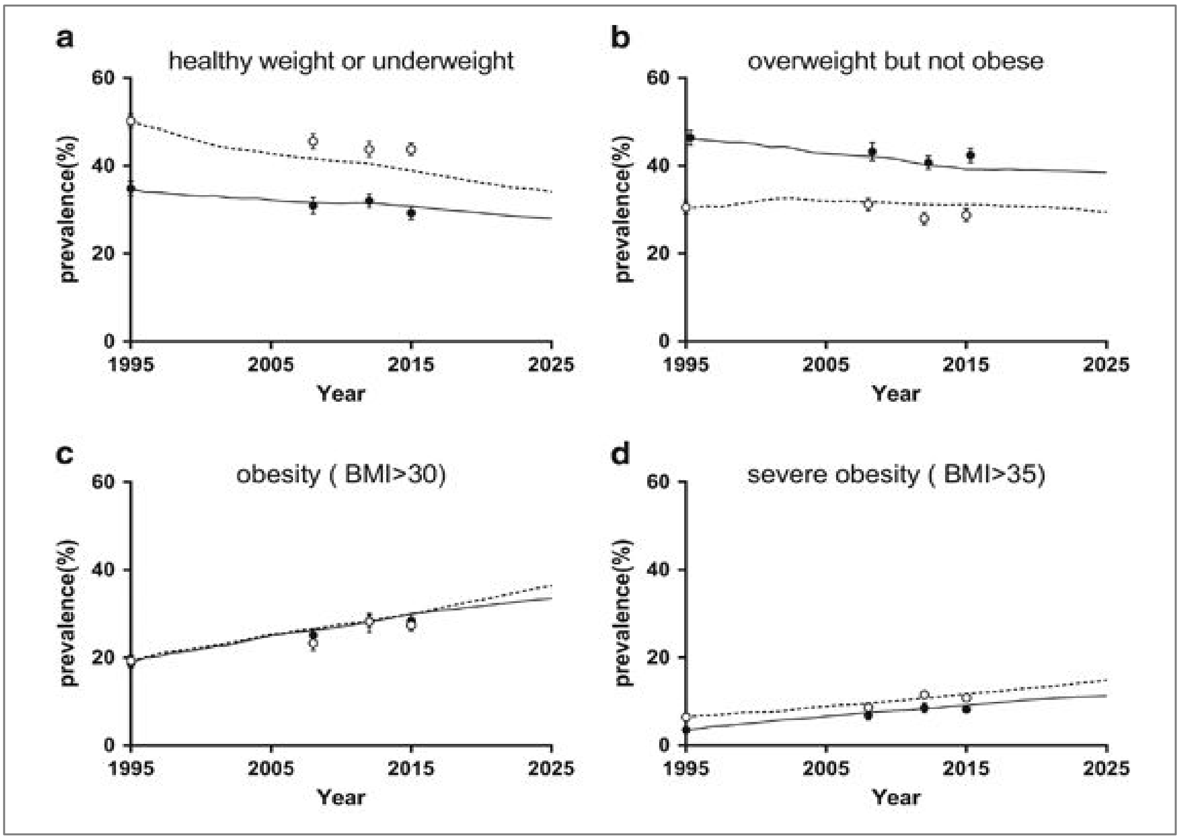


Figure 1.8 Population simulations from 1995 to 2025

Source: Hayes et al., 2017.

1.8 Intervention strategies for obesity

Numerous interventions have been proposed to reduce obesity. These can be broadly grouped into four main categories: lifestyle, education, public policy, and medical (Table 1.5). Some argue that policies that prevent excess weight gain, rather than treating obesity, may be more successful (Hill et al., 2012). Results from a US study investigating the drivers of obesity suggest that approaches to obesity should emphasise a reduction in energy intake (Swinburn et al., 2009). Another recommendation is to address the food environment drivers (processed, readily available, lower-cost food) that have led to an overconsumption of energy (Swinburn et al., 2011).

Lifestyle interventions

Lifestyle-based interventions aim to change individual behaviour around food choices and physical activity, with the aim of reducing nutrient intake and increasing participation in exercise (Roqué i Figuls et al., 2013). These interventions can also be delivered in conjunction with behavioural therapy, including interventions such as counselling or advice, and can be delivered by medical professionals or computer-based.

Table 1.5 Interventions aimed at reducing obesity

Intervention strategy	Types of programs
Lifestyle	Weight-loss programs GP interventions Counselling Web-based interventions
Education	School education Parental education Workplace programs
Medical	Pharmaceuticals Surgery – gastric bypass, gastric banding
Public Policy	
-Health promotion	Media campaign aimed at awareness Subsidise physical activity Subsidise healthy food Financial incentives Increased bike paths and recreation centres
-Regulatory	Food labelling – traffic lights, front/back package labelling Taxes on unhealthy food Ban on commercials aimed at kids

Pharmaceutical interventions

Obesity interventions with a pharmacological agent include drugs that suppress the appetite and inhibit absorption (Roqué i Figuls et al., 2013). Currently in Australia, the only pharmaceutical available on the PBS for obesity is Orlistat. The Australian Family Physician guidelines recommend that pharmacotherapy be used as an adjunct to lifestyle interventions. Other off-label pharmacotherapies include topiramate and phentermine (Ching Lee & Dixon, 2017b).

Surgical interventions

The surgical interventions available for obesity to restrict dietary intake are called bariatric surgery. These surgeries are designed to make the stomach smaller and make the patient feel full after eating smaller amounts of food[7]. The three most common surgeries performed in Australia include sleeve gastrectomy (most of stomach removed), adjustable gastric band (adjustable ring around top part of stomach) and Roux-en-Y gastric bypass (joining a small pouch directly to intestine, bypassing stomach). Bariatric surgery is recommended for individuals with a BMI greater than 40 or individuals with a BMI greater than 35 and one or more obesity-related complications (Ching Lee & Dixon, 2017a).

[7] Guide to bariatric surgery: https://www.healthdirect.gov.au/guide-to-bariatric-surgery

Public policy interventions

Policies, laws and regulations are used to help promote social change. These can include initiatives to encourage healthier behaviours or build healthier environments, laws around the marketing of unhealthy food to children, creating task-forces, nutritional labelling on food products, restricting sale of unhealthy foods in schools, subsidies for healthy behaviours or taxes for unhealthy behaviours (e.g., sugar tax) (Swinburn, 2008).

Governments have implemented a range of policies aimed at combating obesity. The main changes to public policies are: (1) education reforms (school-based policies), (2) food labelling and advertising reforms, (3) health care and training requirements, (4) transport and urban development, and (5) taxes and subsidies (Kuchler et al., 2005). Appendix 2 presents international obesity policies currently in practice.

The Australian government has developed several initiatives to tackle obesity. In 2015, the government invested in the 'Healthy Food Partnership', which aimed to encourage healthier eating by educating consumers on appropriate food and energy intake, portion sizes and awareness of healthier food choices. This has provided support for food manufactures to make positive changes to the food supply (Australian Government Department of Health, 2016) in line with the 'Health Star Rating' system, a ranking system in which all packaged food is ranked from a half star to five stars (Australian Government Department of Health, 2014a). Additionally, the 'Healthy Weight Guide' was introduced in 2014 (and an associated website in 2016[8]) to assist individuals to adopt healthier lifestyles (Australian Government Department of Health, 2014b). The biggest investment has been in programs to encourage exercise for children, with more than $100 million provided for the 'Sporting Schools Initiative'.

These initiatives fall within the education and regulatory categories. Other national bodies have outlined recommendations that include a number of intervention strategies. The Australian Council of Presidents of Medical Colleges (CPMC) has outlined a set of interventions and regulations to tackle obesity (Table 1.6) (CPMC Summit on Obesity, 2016).

[8] Department of Health: www.healthyweight.health.gov.au/

Table 1.6 Recommendations from the National Health Summit on Obesity (2016)

Life course considerations • Promoting the intake of healthy foods at all ages • Weight management • Preconception and pregnancy care • Early childhood diet and physical activity • Health, nutrition and physical activity for school aged children
Regulatory mechanisms • Taxation on sugar • Advertising restrictions • Clear and specific food labelling • Regulating sale of fast food in schools, sporting venues and other high-risk locations
Lifestyle and behaviours • Promotion of physical activity exercise and play • Dietary guidelines freely available and distributed through multiple conduits • Health professionals to provide opportunistic advice
Environmental considerations • Pedestrian pathways • Cycle ways
Adjunctive therapies: • Surgery • Medication • Psychological support and dealing with stigma.

Source: CPMC Summit on Obesity, 2016.

Although these recommendations are based on those previously published by national and international regulatory bodies, it is not clear which, if any, are based on rigorous evidence of effectiveness using scientific methods and analysis. Based on extensive global research, the Global Burden of Disease (GBD) Global Obesity Collaborators have suggested 'the implementation of multicomponent interventions to reduce the prevalence and disease burden of high BMI' (GBD Obesity Collaborators, 2017). The issue for decision-makers is that policies alone are unlikely to reduce the prevalence of overweight and obesity, as the required lifestyle changes are at the individual level (Chan & Woo, 2010). The evidence indicates that increased physical activity and reduced consumption of high caloric foods reduce weight for an individual (Hill et al., 2012), but the evidence is lacking on the effectiveness of these interventions at a population level. It is, therefore, important to focus on the motivation for behaviour change through individual lifestyle modifications. Broadly, this is the focus of this thesis.

Evaluating the effectiveness of individual-level interventions aimed at changing 'lifestyle', i.e., the amount and type of food individuals consume and the amount and type of exercise they undertake, is an important contribution to reducing obesity. In an ideal setting, the evaluation of these interventions using randomised controlled trials would provide the best evidence, but for many of the recommended initiatives this is not possible. Due to the complex aetiology of obesity, it is likely that a wide range of interventions is needed to reduce its prevalence. Furthermore, a multi-disciplinary approach may be necessary to evaluate proposed recommendations and provide evidence of effectiveness.

1.8.1 Individual level lifestyle interventions

A comprehensive systematic review and meta-analysis of 80 studies found that weight-loss interventions consisting of reduced-calorie diet and exercise were associated with moderate levels of weight loss after six months (Franz et al., 2007). Adding a weight-loss medication improved weight-loss maintenance. Figure 1.9 illustrates the two-year weight loss results reported in the meta-analysis.

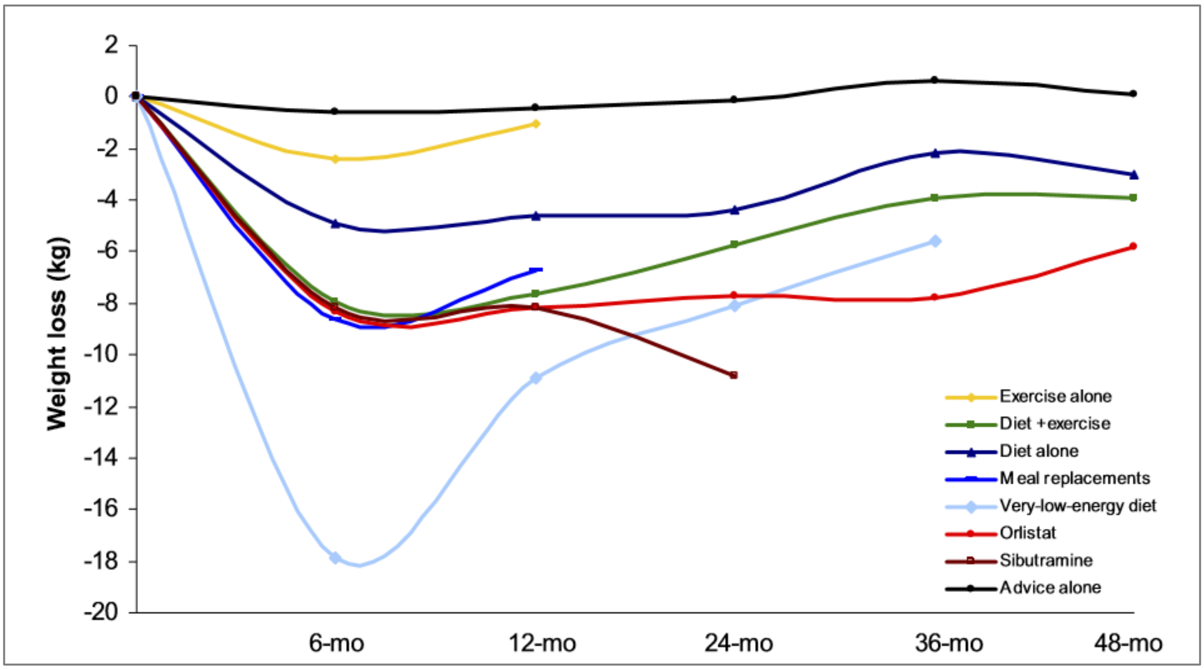


Figure 1.9 Average weight-loss of subjects completing a minimum one-year weight-management intervention (review of 80 studies)

Source: Franz et al., 2007.

Overall, the study found that weight-loss interventions comprising diet alone, a combination of diet and exercise, meal replacements, and weight-loss pharmaceuticals combined with diet had the most significant effect on weight loss. However, at approximately six months weight loss appears to level off. Interestingly the authors found that exercise alone or weight loss advice (in the form of booklets, brochures, manuals or individual advice) did not result in successful weight loss (Franz et al., 2007). A more recent meta-analysis found that weight-loss diets (comprising low fat and or low saturated fat foods) for adults with obesity ‘may reduce premature all-cause mortality, regardless of any exercise requirements’ (Ma et al., 2017).

1.9 How can economics help?

The increased prevalence of overweight and obesity is not only a major public health concern but is also an economic problem (Philipson & Posner, 2008). Obesity is in part due to the decisions individuals make with regards to food and exercise. When obesity is regarded only as a public health issue, the recommendation is for government intervention. However, from an economic point of view there is no reason for the government to intervene if individuals are being rational and maximising their utility (Mann, 2006). Given that economics is the study of human decision-making, understanding the underlying causes of obesity is important to properly target policy initiatives to change underlying behaviour. The remainder of this chapter will focus on the economic theories and concepts used in the thesis.

1.9.1 Rational utility theory

Traditional economic theory is predicated on a ‘market’ approach, which assumes that individuals make rational decisions based on their preferences to maximise utility (well-being) (Mann, 2006). In a rational utility model, a ‘perfect market’ exists within which individuals maximise their utility given their constraints (money and time). In terms of obesity, food is bought and sold in a consumer market and individuals know how much energy they need and how much to expend (Karnani et al., 2016). Furthermore, individuals’ choices are considered optimal and do not require intervention (Dodd, 2008). In reality however, individuals make choices in an ‘unconscious and impulsive manner’ that would not always be considered rational. For example, the literature reports that obese individuals have higher levels of depression, which defies traditional theory which would assume that obese individuals are maximising their satisfaction (Mann, 2006).

Furthermore, standard economic theory assumes that an individual’s revealed preferences reflect their true preferences, which may not hold when trying to understand obesity (Heshmat, 2011). Behavioural economics, which combines insights from both psychology and economics, suggests that revealed preferences cannot be relied on to explain choices in terms of well-being. Behavioural economics can provide a framework under which eating/exercise behaviour and obesity can be evaluated. Understanding an individual’s behaviour when their choices and decisions deviate from the rational model may assist the design of interventions aimed at reducing the prevalence of obesity. From a policy perspective, the aim is to change 'unhealthy' behaviours and influence people to maintain and sustain healthy living. However, it is unclear whether individuals are altering their responses due to changing economic incentives. From an economic perspective, when people are behaving irrationally it means there are market failures that need to be fixed to achieve economic efficiency.

It has been argued that policies that make it easier and cheaper to eat a healthy diet and engage in regular physical activity are required to combat obesity (Finkelstein & Strombotne, 2010). The difficulty is in deciding which interventions will have the greatest impact. At a microeconomic level, people make choices to maximise their utility. If the goal is to maximise their health, lifestyle choices become an input into their utility function. At a macro level, it is necessary to understand the reasons behind the increasing trend in obesity rates in order to develop solutions and to target policy recommendations appropriately. There are two important priority areas in which economics can inform the research on obesity:

1. Rationale for policy intervention
    a. Fix market failures
2. Theoretical framework for understanding human behaviour
    a. Optimal design of incentives and trade-offs for weight-loss
    b. Understand the factors that contribute to obesity
    c. Assess the cost-effectiveness of programs and policies.

1.9.2 Market failure

It has been hypothesised that the reason market failures are to blame for the rise in obesity rates is due to individuals changing their utility maximisation approach in response to changing economic conditions (technological change, societal progress) (Courtemanche et al., 2015b). Three market failures have been identified as possible contributors to the obesity epidemic: negative externalities, imperfect information and irrational individual behaviour. From an economic perspective, the government should intervene to correct these market failures when they occur (Finkelstein & Strombotne, 2010).

Negative externalities of obesity

An externality is a spill-over effect from the consumption of a good. A negative externality is an external cost borne by a third party. A common example is that cigarette smoking leads to passive smoking, which can have negative effects on third parties. These external costs then affect overall social welfare. Cawley (2015) asserts that many of the costs of obesity are paid for by non-obese individuals, through public and private health insurance, given that the premiums (for private health insurance) or taxes (for public health insurance) paid by individuals are the same regardless of weight (Cawley, 2015). In both scenarios, healthy weight individuals are subsidising the healthcare costs of obese individuals.

Implementing incentives in private health insurance schemes through rewards or penalties addresses the negative externalities imposed through the pricing of health insurance. In countries where there is a public healthcare system, as in Australia, finding equitable solutions is more difficult. A common solution to externalities caused by obesity is to apply a tax that increases the cost, thus reducing the externality. Using economic theory, this 'fat tax' would raise the price of unhealthy food and should result in a reduction in consumption of that food (Mann, 2008).

It appears however, that measures such as soda taxes increase the probability that individuals will substitute other higher caloric beverages (Fletcher et al., 2010). Moreover, an excise tax on unhealthy foods differs from the successful taxing of cigarettes, where the marginal damage of smoking is constant. Taxing unhealthy foods does not address the fact that eating in moderation can have positive outcomes, or that unhealthy foods are also consumed by non-obese individuals. Recent studies have found that increases in the price per calorie have an insignificant effect on BMI in the short term but may have better long-term success (Goldman et al., 2011). A further study of taxing snack foods found that high tax rates would not change current consumption, but would generate a source of tax revenue (Kuchler et al., 2005). Another issue with taxing unhealthy food is that if the tax were to be removed at any point in the future this could encourage more consumption of the good.

Imperfect information

While most economic theory assumes complete information, a lack of information may be a contributing factor to the rise in obesity levels. It is likely that individuals underestimate the risk of becoming fat (Coestier et al., 2005). The perceived disadvantages of obesity do not outweigh the pleasure of unlimited eating and no exercise. Another potential informational failure is that obese individuals do not understand the caloric content of the meals that they are consuming. It is well-established that individuals underestimate the calories in restaurant meals (Block et al., 2013).

Furthermore, overweight and obese individuals may not fully understand the long-term health implications of excess weight. This type of information is often under-provided in a competitive market, as it can be considered a public good (Dodd, 2008). An example of a policy aimed at providing better information is food-labelling regulations. Such interventions include nutrition labelling (clear display of serving size, calories or added sugars) or traffic-light label systems, which code food into red, amber and green based on levels of saturated fat, salt, sugar and calories. Overall, the evidence of the impact of these interventions on weight is lacking (Storcksdieck, Genannt, Bonsmann & Wills, 2012).

Irrational inconsistent behaviours

This type of market failure occurs when individuals make irrational choices or are incapable of making choices for themselves (Cawley, 2015). Irrational behaviour mostly refers to children, as the choices they make with regards to food and physical activity are not considered rational (as opposed to adults). Government interventions include school lunch programs and limited access to unhealthy foods within schools (McCarthy, 2004). Another intervention suggested for this market failure is bans on (unhealthy) food advertising to children.

1.9.3 Theoretical framework

From an economist's point of view, market failure does not apply to individuals. The market failures discussed above are related to external factors (outside the control of the individual), and government intervention is warranted. Where a public health advocate views obesity as individuals making bad choices and trying to change them, an economist sees rational individuals making trade-offs between health and pleasure, income or time, which in turn lead to increases in body weight. Thus, understanding the trade-offs individuals make and the optimal incentives required to change behaviour is one contribution economics can make to obesity research. The results of this type of research will inform the development of interventions targeting these behaviours. Within a limited health care budget, it is imperative that greater focus be placed on determining which interventions or prevention strategies are the most effective and cost-effective.

Incentives

In the context of programs targeting individuals, one approach is to provide financial incentives to encourage people to lose excess weight. From an economics perspective, the following reasons have been proposed for these failures: (1) the benefits of weight loss are not always obvious (i.e., the loss of or lower levels of QoL is not perceived as an opportunity cost); (2)

the benefits of weight loss are not realised immediately; and (3) preferences are discounted hyperbolically resulting in inconsistent time preferences (Cawley & Price, 2011). A comprehensive review of financial incentives to change behaviour demonstrated that the majority of studies were effective in changing behaviour (Kane et al., 2004). However, the evidence is not as compelling for weight-loss interventions. A meta-analysis of nine RCTs of incentives to lose weight did not find a statistically significant weight loss due to financial incentives (Paul-Ebhohimhen & Avenell, 2008). A more recent review of financial incentives demonstrated their usefulness in the short-term, but more evidence is needed for long-term results (Ananthapavan et al., 2018).

Time preferences

Through the lens of time preferences, individuals can be perceived as engaged in short-term eating and physical activity habits that give them pleasure whilst ignoring the long-term effects of these decisions. Choosing to consume an unhealthy diet could reflect a preference for myopic (present) consumption (Robb et al., 2008). An individual will trade off the disutility of extra weight for the enjoyment they receive from eating energy-dense foods and having sedentary lifestyles. There is a constant weighing-up of the costs and benefits of diets and physical activity to maximise utility, subject to both time and income constraints. The issue arises due to a time differential, in which the 'enjoyment from eating and sedentary activities occurs in the present while the health costs occur in the future' (Courtemanche et al., 2015a).

Economic evaluation

The fundamental problem economists are trying to solve is how to allocate scare resources between competing demands, while distributing these resources efficiently and equitably. The field of health economics aims to determine the best allocation of limited resources to obtain a maximum 'health improvement'. Given a limited health care budget, it is essential that the cost-effectiveness of new programs aimed at obesity is included in the decision-making process and funding allocated to those programs that offer the best returns (in terms of QoL) for the least cost. For this reason, assessing the cost-effectiveness of interventions and policies targeted at overweight and obese individuals is an important aspect in the research of the economics of obesity.

1.10 Aims and Objectives

Based on the discussions above, the overall aim of this thesis is to explore issues of rational behaviour in the context of lifestyle interventions designed to address overweight and obesity.

The objectives are to provide a review and critique of the current economic evaluations of obesity interventions, understand the factors that contribute to obesity (specifically focusing on QoL), investigate the extent to which interventions are aligned to the preferences of overweight and obese individuals, and, finally, study the effects of time preferences and trade-offs on obesity. The specific research questions are:

1. Are current economic evaluations of obesity interventions accurately assessing the overall cost-effectiveness of interventions?
2. Is QoL being accurately measured in economic evaluations of obesity interventions?
3. Does QoL improve with weight loss to the same magnitude of the initial loss in QoL?
4. Are there factors other than changes in weight that could be influencing QoL in people who are obese?
5. Are obese individuals' preferences for weight-loss programs different from those of normal-weight individuals?
6. Do obese individuals have different time preferences that impact on their propensity to be obese?

1.11 Structure of the PhD

The thesis will be presented over six chapters and provide insight into each research question. The structure of how the thesis will be presented is summarised in Table 1.7. Chapter 2 will discuss the economic evaluation of obesity interventions and present a targeted review of behavioural interventions. In the chapters exploring health-related QoL (chapters 3 and 4) the results of econometric analyses of a large Australian longitudinal survey, the Household Income and Labour Dynamics in Australia Survey (HILDA) will be reported. The results of a survey conducted during the thesis that included a discrete choice experiment (DCE) and time preference elicitation methods will be reported in chapters 5 and 6. In Chapter 7, the overall results will be summarised and areas for future research will be highlighted.

Table 1.7 Thesis outline by chapter

Chapter	Description	Research question
Chapter 2	Review of cost-effectiveness of behavioural weight-loss interventions	1, 2
Chapter 3	Relationship between obesity and QoL	3
Chapter 4	Exploring the endogeneity between QoL and obesity	4
Chapter 5	Preferences for weight-loss interventions: a DCE	5
Chapter 6	Time preferences of obese and normal weight individuals	6
Chapter 7	Discussion: overall conclusions and implications	1-6

2 ECONOMIC EVALUATION OF OBESITY INTERVENTIONS

The overall aim of this chapter is to review the current research on the cost-effectiveness of behavioural obesity interventions and assess the modelling inputs and overall claims of cost-effectiveness. A secondary aim is to evaluate the QoL inputs that are being used in current economic evaluations of obesity interventions. The chapter concludes with a critique of the methods and data sources used and a discussion of potential sources of bias in the current models.

One important area in which economic research can be useful is determining the effectiveness and cost-effectiveness of interventions aimed at reducing the rate of overweight and obesity. Considering that healthcare resources are scarce, there exists an 'opportunity cost' when choosing an intervention over the next-best alternative. Roux and Donaldson (2004) propose that the key question we should be trying to answer is, 'what intervention which aims to treat this health problem is the best buy?'. Although there are potentially unlimited needs for health care, expenditure is constrained by limited resources. Choosing an intervention over the next best alternative creates an 'opportunity cost'. For example, how is a decision made between funding a high-cost drug that could save the lives of a few patients versus funding a public health intervention that could reduce smoking uptake? How are the outcomes of each intervention valued? Decision-makers need tools to help evaluate and prioritise competing options. Decisions made to implement an intervention are based on its being effective and cost-effective. For this reason, assessing the cost-effectiveness of interventions and policies targeted at overweight and obese individuals is an important aspect of research into the economics of obesity. The aim of such research is to ensure funds are allocated appropriately in the decision-making process by identifying those programs that offer the best returns in terms of long-term health benefits whilst reducing the costs associated with obesity.

Many health policy decision are based, at least in part, on the results of cost of illness (COI) studies, which describe, measure and predict the societal burden of a condition – in this case, obesity – in monetary terms (Moodie & Carter, 2010). However, it has been argued that COI studies have limited value in aiding the efficient allocation of heath care resources, as they do not take into account the gains made due to interventions and may result in decision-makers ignoring potentially cost-effective interventions such as those that may produce fewer health gains but which are low cost (Byford et al., 2000). Roux and Donaldson (2004) argue that these studies do not help in terms of reducing obesity, other than confirming that obesity is a major and potentially costly public health concern. Researchers have proposed that the contribution of economics to the study of obesity should refocus research from measuring the economic burden of obesity to evaluating strategies to prevent and treat obesity through formal economic evaluation (Roux & Donaldson, 2004). This echoes Stefan Mann's sentiments that economists should focus on suggestions about how to tackle the obesity problem, as opposed to the evaluation of its costs (Mann, 2008). Moreover, the economic evaluation of a range of interventions across multiple settings may be more useful than economic evaluations of single interventions, given policy-makers are constrained by limited resources and need to apportion these resources across multiple public health priorities (Moodie & Carter, 2010).

2.1 Economic evaluation

Economic evaluation is a tool used in health economics that compares the costs and consequences of options (Drummond, 2005). The results of an economic evaluation do not provide a 'value' for one intervention/program; rather, the relative value of alternative programs is estimated by comparing the 'new' or proposed intervention/program with at least one alternative option (Briggs, 2006). The results of economic evaluations are presented in terms of an incremental cost-effectiveness ratio (ICER), which compares the benefits and costs of an intervention/program against a comparator (for example, usual care).

The resulting ICERs can then be plotted on a cost-effectiveness plane, which presents the results in terms of effectiveness and costs relative to the comparator (Figure 2.1). If the ICER is in the south-east (SE) quadrant, the intervention is considered both more effective and less costly than the comparator; therefore, the intervention is 'dominant' and considered to be cost-effective. The opposite occurs when the ICER is in the north-west (NW) quadrant. In this scenario, the intervention costs more and is less effective than the comparator, and the intervention is considered 'dominated' and rejected. However, it is common for ICERs to fall in the north-east (NE) quadrant, where the new intervention is more effective, but costs more than the comparator. In this case, the ICER is evaluated against a willingness-to-pay threshold (λ) to evaluate whether the additional benefit is worth the additional cost. For ICERs falling in the south-west (SW) quadrant, where the intervention is estimated to cost less than then comparator but the benefit is also lower, decision-makers need to weigh up whether to accept a lower-cost, less effective intervention, if the resources released by adopting the less effective intervention can be used to maximise total health elsewhere (i.e., the opportunity cost approach).

	Intervention is more costly		
Intervention is less effective	**NW quadrant** Intervention dominated *more costly, less effective* *reject*	**NE quadrant** Consideration of ICER *cost per gain in benefit*	**Intervention is more effective**
	SW quadrant Consideration of ICER *Cost savings per reduction in benefit*	**SE quadrant** Intervention is dominant *less costly, more effective* *accept*	
	Intervention is less costly		

Figure 2.1 Cost-effectiveness plane of effectiveness and costs
Source: Robertson et al., 2014.

The health outcomes commonly used in economic evaluation include life years gained, DALYs and QALYS. Other, more specific, measures may also be used, including outcomes such as hospitalisations, deaths avoided, strokes avoided etc. Determining the relative cost-effectiveness of interventions based on the latter outcomes requires an implicit valuation of what a hospitalisation or stroke avoided is worth. Because these outcome measures are not comparable across a range of healthcare interventions, a generic measure is necessary to allow the evaluation of competing options across multiple disease areas. QALYs combine both mortality (in terms of survival) and morbidity (in terms of QoL) into one generic measure, which enables comparisons across different diseases and interventions.

2.1.1 Quality-adjusted life years

The QALY was developed to measure the impact of an intervention on both the extension of life and QoL and combines these outcomes into one measure. It provides a summary measure of health outcomes for use in economic evaluation, most commonly in the type referred to as cost-utility analysis, and has become the dominant outcome measure for economic evaluations (Torrance, 1986; Williams, 1985). The QALY is used as the outcome measure in reimbursement submissions to Health Technology Assessment (HTA) agencies such as the

Pharmaceutical Benefits Advisory Committee (PBAC) in Australia, National Institute for Health and Care Excellence (NICE) in the UK, the European Network for technology assessment (EUnetHTA) and the Canadian Agency for Drugs and Technology in Health (CADTH) in Canada (Whitehead & Ali, 2010; Boyers et al., 2015). To generate QALYs, health utility values are applied in the evaluation, representing preference weights for a particular disease or health state. Health states with higher QALY weights indicate better (more preferable) states. Health utilities are measured on a scale of 0 to 1, where 0 is death and 1 equals full health (Whitehead & Ali, 2010). It is possible to have negative values for those states that would be considered worse than death. Utility weights can be measured using direct measures such as a time trade-off (TTO), standard gamble (SG), visual analogue scale (VAS) or discrete choice experiments (DCEs) (Brazier et al., 2007). They can also be elicited through generic instruments such as the SF-36, Euro-QoL, HUI and AQoL. Figure 2.2 illustrates how QALYs are measured when comparing a treatment with no treatment. The difference between the 'treatment (A)' and 'no treatment (B)' arms of the study represents the QALYs gained.

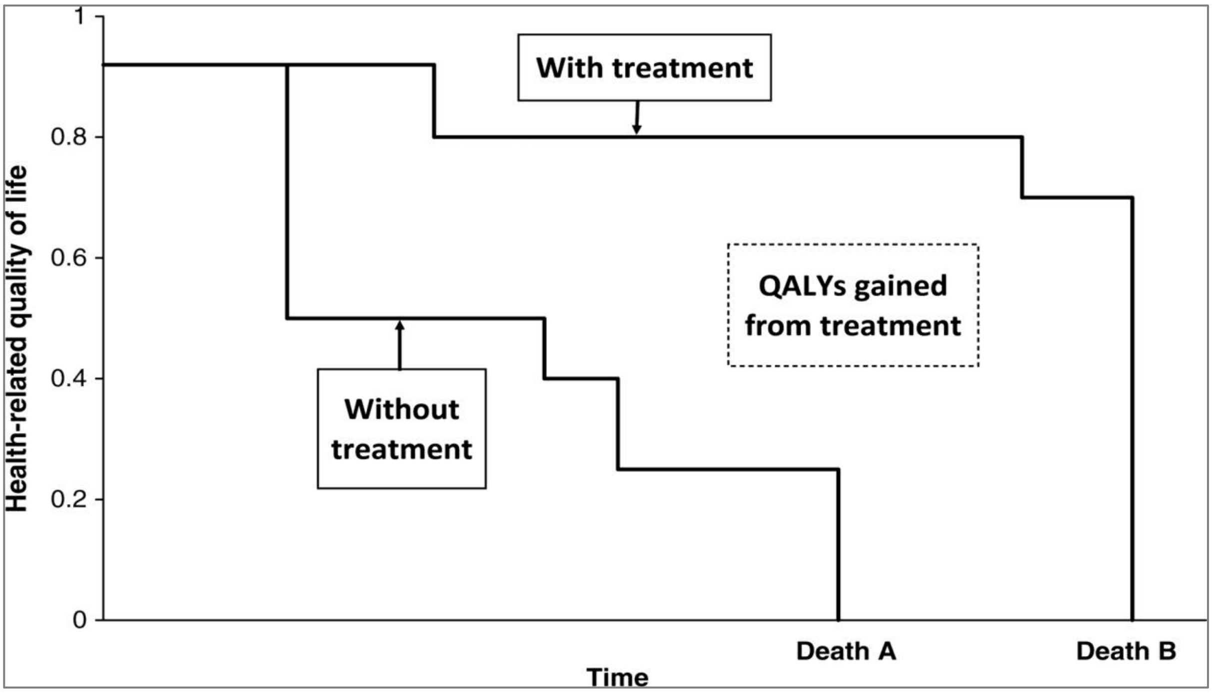


Figure 2.2 Diagram of QALYs gained from treatment vs no treatment

Source: Whitehead and Ali, 2010.

One issue with current economic evaluations occurs when QALYs are estimated using data collected alongside trials. In most cases, these data are required to be extrapolated and incorporated into lifetime models. Regression to the mean can further impact results, as trial participants with lower QoL at baseline may have larger gains than those with higher QoL at baseline. This is particularly true when the instrument used to estimate the QoL has a large variance (Vickers & Altman, 2001). Figure 2.3 presents the typical application of QoL captured in a clinical trial, showing the difference in gains in QoL between the intervention and the control. The area between the two curves represents the QALY gain between the two treatments and the relative QALY gain is extrapolated past the time length of the study period (denoted by the shaded area). Given that many of the potential comorbidities due to obesity arise in the future, the use of QoL values from short-term trials of interventions will not capture the effect on QoL when applied in economic evaluations.

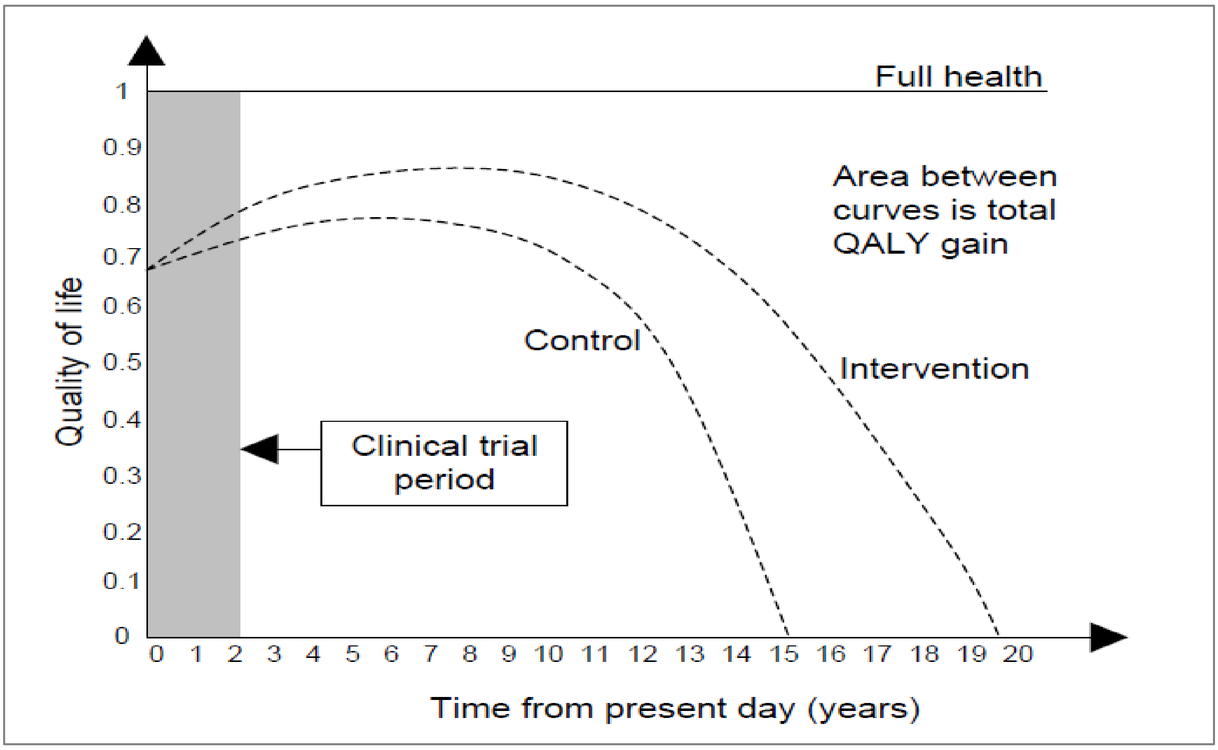


Figure 2.3 QoL captured in clinical trials

Source: Edwards et al., 2004.

2.1.2 Markov models in cost-effectiveness analysis

Many economic evaluations employ Markov models to estimate future costs and outcomes that can be attributed to a particular intervention. These models are particularly useful for modelling the effect of interventions on chronic diseases over time by tracking changes in QoL and the cost of a disease over time across different interventions. Markov models are a type of state transition model that assumes individuals are, at any one time, in only one of a fixed number of discrete health states, called *Markov states*. Any movements between states are represented by a *transition probability* (Sonnenberg & Beck, 1993). The time horizon of the model is broken into equal time periods (for example, one year), which is termed the *Markov cycle*. Each state is assigned an estimated health outcome and resource use; then, with the associated transition probabilities, the long-term costs and long-term outcomes that are associated with a disease can be estimated for a specific intervention (Briggs & Sculpher, 1998). Markov models are also inherently 'memoryless', where the transition probability out of a state does not depend on any previous states the individual occupied, often referred to as the *Markovian assumption.* Figure 2.4 demonstrates a state transition diagram of a hypothetical Markov model using BMI categories to represent normal weight through to severely obese health states

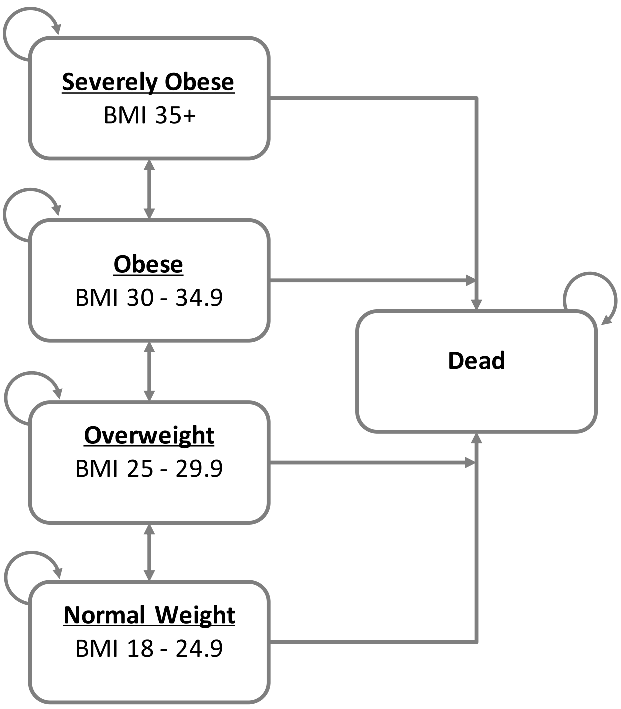


Figure 2.4 Markov model diagram with BMI categories

The arrows in the diagram represent the transitions that can occur for a cohort of patients between the five Markov states. The states in a Markov model are mutually exclusive, meaning that individuals can only be in one state at any given point in the model. In each of the BMI categories there is a risk that individuals will die, remain in the same BMI category or transition to an adjacent BMI category (gain weight or lose weight). The death state is considered an *absorbing state*; once an individual enters this state, they remain in this state for the length of time the model is run.

In cost-utility models, QoL is attributed at the state level. The expected utility can be represented by the following equation where both survival in years and QoL are incorporated:

$$Expected\ utility = \sum_{s=1}^{n} t_s * u_s \tag{2-1}$$

where t_s is the time spent in state s and u_s is the utility weight assigned for state s. In a Markov model, t_s will track survival in terms of life years in that state and u_s is the quality weight of those years of survival. To illustrate the calculation of QALYS, consider the following utility values assigned to the severely obese, obese, overweight, normal-weight and death states respectively: (0.68, 0.70, 0.78, 0.79, 0.0). Within a ten-year time period, a person who is obese in the first year, then transitions to overweight for two years, then transitions and remains in the normal state for seven years would accumulate 7.79 QALYs [(0.70 x 1) + (0.78 x 2) + (0.79 x 7)]. On the other hand, a person who is severely obese for five years then transitions to the death date would accumulate 3.4 QALYs [(0.68 x 5) + (0 x 5)]. It is important that the utility value assigned to each state accurately reflects the QoL associated with that state so the resultant cost-effectiveness estimates are also accurate.

2.1.3 Limitations of economic evaluation in the context of obesity

Economic evaluation has a number of limitations, some of which apply to obesity interventions. Many economic evaluations of obesity interventions assume that weight loss will reverse the negative health consequences of excess weight, which may not properly capture the health impacts of obesity (Roux & Donaldson, 2004). Furthermore, some evaluations assume the gain in utility from an intervention is comparable to the QoL of a normal weight individual, which overestimates the benefit received from the intervention. This assumption may over-simplify the weight loss process, by assuming disease risk and QoL return to the levels of someone who has never been overweight or obese

QALYs only take into account health-related benefits and do not include individual preferences. The measure of utility captured in a QALY diverges from the definition of utility in neoclassical economic theory.[9] In addition, an understanding of people's preferences for health programs and outcomes is likely to be needed to design effective health policies (Viney et al., 2002). Economists commonly use revealed preferences (RP) to provide information about consumer preferences for goods and services (Lancsar & Louviere, 2008). Viney et al. (2002) note that it is not always possible to use RP data in health economics research, as consumers rarely encounter market prices for health care. Thus, it is not always apparent whether the consumption of healthcare goods and services reflects consumers' preferences. Furthermore, it is difficult to disentangle the effect of individual characteristics such as age and previous experiences from RP data, as they are highly correlated (Rohr, 2006).

2.2 Review of cost-effectiveness of obesity treatments

As discussed in Section 1.8, multiple interventions have been undertaken to reduce the prevalence of obesity, including behavioural, public health, pharmaceutical and surgical interventions. Many systematic reviews of economic evaluations of surgical and pharmacological therapies and public health programs have been published. A comprehensive review of individual behavioural interventions was not identified; for that reason, the review conducted in this chapter focuses on behavioural interventions. However, the systematic reviews of economic evaluations of pharmacological, surgical and public health interventions will be discussed and evaluated.

2.2.1 Systematic Reviews

Twenty systematic reviews were identified during the literature search. These included a mix of cost-effectiveness analyses of lifestyle, community, behavioural and public policy interventions aimed at overweight and obese individuals. After assessing all reviews, 13 were considered to be applicable (presented in Table 2.1). Seven studies were excluded from the review due to the inclusion of an incorrect patient group, only considering effectiveness and reviewing only one study (Gandjour, 2012; O'Meara et al., 2001; O'Meara et al., 2002; Picot et al., 2012; Foxcroft & Milne, 2000; Pavey et al., 2011; Nguyen et al., 2001). Of the 13 included systematic reviews, nine were identified during the literature search and four were discovered from the reference lists of the identified reviews (pearling).

[9] Neoclassical economic theorises that all individuals in an economy behave rationally, maximise their utility and act independently. The QALY is a departure from this as it does not include all attributes or reflect social values (Drummond et al., 2015).

Table 2.1 Systematic reviews of interventions aimed at reducing obesity

Study	Year	Focus of review	Title
Clegg	2003	Surgery	Clinical and cost-effectiveness of surgery for morbid obesity: A systematic review and economic evaluation
Avenell	2004	Surgery Pharmaceutical Behavioural	Systematic review of the long-term effects and economic consequences of treatments for obesity and implications for health improvement
Dixon	2004	Utility values	Utility values for obesity and preliminary analysis of the Health Outcomes Data Repository
Salem	2005	Surgery	Are bariatric surgical outcomes worth their cost? A systematic review
Neovius	2008	Pharmaceutical	Cost-effectiveness of pharmacological anti-obesity treatments: A systematic review
Picot	2009	Surgery	The clinical effectiveness and cost-effectiveness of bariatric surgery (weight loss) surgery for obesity: A systematic review and economic evaluation
Ara	2012	Pharmaceutical	What is the clinical effectiveness and cost-effectiveness of using drugs in treating obesity in primary care? A systematic review
Griffiths	2012	Surgery Pharmaceutical Behavioural	Economic Evaluations of adult weight management interventions: A systematic literature review focusing on methods used for determining health impacts
Lehnert	2012	Behavioural	The long-term cost-effectiveness of obesity prevention interventions: Systematic literature review
Terranova	2012	Surgery	Bariatric Surgery: Cost-effectiveness and budget impact
Boyers	2015	Lifestyle/Pharmaceutical	A systematic review of the cost-effectiveness of non-surgical obesity interventions in men
McKinnon	2016	Public policy	Obesity-related policy/environmental interventions: A systematic review of economic analyses
Schwander	2016	All	Systematic review and overview of health economic evaluation models in obesity prevention and therapy

Although multiple reviews have been published assessing the cost-effectiveness of behavioural interventions in individuals with obesity, no systematic review containing all the relevant economic evaluations was identified. Although five systematic reviews (Avenell et al., 2004; Boyers et al., 2015; Griffiths et al., 2012; Lehnert et al., 2012; Schwander et al., 2016) were identified, none fulfilled all criteria for inclusion in the review. Therefore, a review targeting economic evaluations of behavioural interventions was conducted. The studies included in the systematic reviews were reviewed to ensure all relevant CUAs were identified.

2.3 Methods

2.3.1 Literature review

The aim of the literature review was to identify economic evaluations presenting cost-utility analyses (CUA) of behavioural interventions in obese adults and assess the methods used to estimate the cost-effectiveness. The inclusion and exclusion criteria are provided in Table 2.2.

The analytic methods and assumptions pertaining to changes in weight, utility, QoL, and comorbidities associated with obesity in the economic evaluations were appraised, as well as the claims of cost-effectiveness.

The initial search was conducted in January 2013 and updated in May 2015 and on 1 February 2017. Searches were conducted in MEDLINE, Embase, NHS EED and Health Technology Assessment (HTA) databases and the Science Citation Index. A further search was conducted on the Tufts Medical Centre Cost-Effectiveness Analysis (CEA) registry[10]. The search string included the terms *'*obesity', '*overweight', 'bmi', 'body mass index', '*cost effectiveness analysis', *cost utility analysis', 'qaly'* and *'*economic evaluation'*. The full search strategy used in the review is provided at Appendix 3.

Table 2.2 Inclusion and exclusion criteria for the literature search

Inclusion criteria	Exclusion criteria
Cost-utility studies of behavioural interventions.	Cost studies, cost-effectiveness studies without the use of utility weights
Studies after 1995	Studies before 1995
Adults aged 18 years or older	Children or adolescents
QALYs included as an outcome	Outcome expressed as cost per LYG, per kg lost, per BMI unit, DALYs
Decision analytic models conducted alongside a trial or de novo models comparing costs and outcomes	Models that did not compare costs and outcomes
Full modelled report available	Abstract form only

The search identified studies published after 1995. The extensive time period was selected to ensure that a complete picture of methodological changes over time was captured. The search was limited to an adult population. Studies that did not present comparisons with alternative treatments were excluded, as the results do not provide true assessments of cost-effectiveness and are not useful for decision-making. One of the goals in treating obesity is to improve QoL (Blissmer et al., 2006), therefore only CUAs that expressed results in terms of QALYs gained were included. CUAs that compared behavioural interventions with other interventions (or usual care) and provided details of the costs and outcomes were selected for inclusion. Outcomes that were not expressed in terms of QALYs were excluded.

[10] Tufts Medical Center, CEA Registry: http://healtheconomics.tuftsmedicalcenter.org/cear4/Home.aspx. Search terms used in Tufts: BMI, obesity and overweight.

2.3.2 Data extraction and review

Data were extracted from the publications identified for full review. Where available, the following data were extracted from each study: year of study, country and perspective, type of model, intervention(s), comparator(s), time horizon, weight assumptions, utility values, utility source, ICER, range around ICER, sensitivity analyses conducted, variable with biggest effect on ICER, and funding source. A quality score was extracted for the studies included on the Tufts CEA registry, which reports a quality value (from 1 to 7) for cost-effectiveness analyses. The ICERs were all reported in 2015 US dollars to correlate with the Tufts registry. A summary of the data extracted from each individual publication is provided at Appendix 4.

2.3.3 Identification of studies

In total, 174 studies were identified in the review process, with 65 studies initially identified through database searches. A summary of the results of the literature search is provided in Table 2.3. After reviewing the titles and abstracts, 96 publications were identified for full-text review. The reference lists of all publications identified for inclusion or further inspection were reviewed to identify any additional publications that may have been missed in the search of the databases. After reviewing the primary studies, 109 additional studies identified via a manual search were included. A flow-chart presenting the study selection is presented in Figure 2.5.

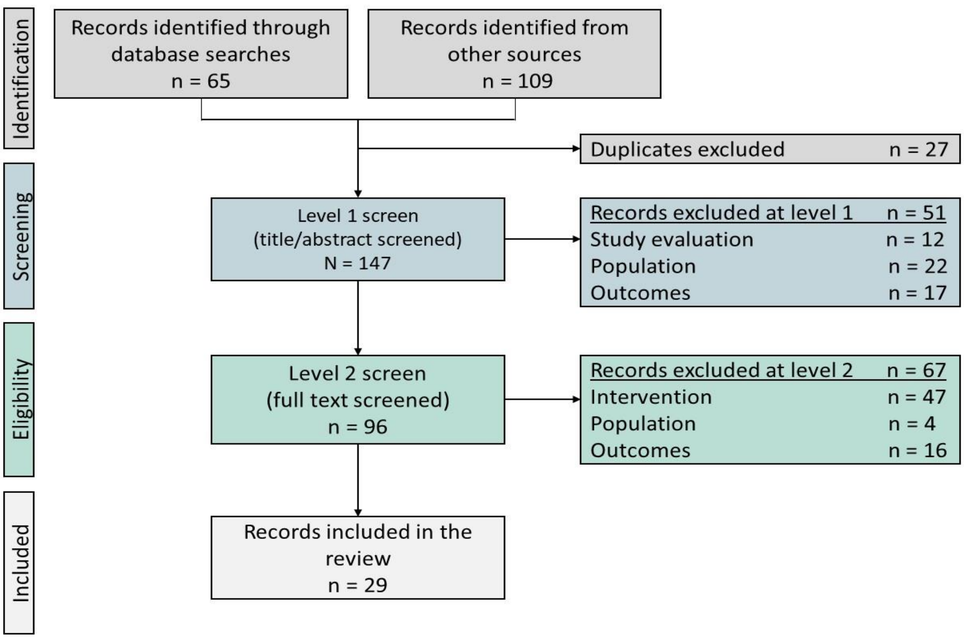


Figure 2.5 Flow diagram of study selection

2.4 Results

In total, 29 studies were identified as having cost-utility analyses that met the inclusion criteria. Eleven of the studies were specifically identified through database searching, another 15 from the reference lists of the systematic reviews and three from the Tufts registry and other sources (Table 2.3).

Table 2.3 Source of papers included in the review

Identification of papers	N
Studies identified through database searching	11
Studies identified through reference lists from systematic reviews	15
Studies identified by the Tufts CEA registry	2
Studies identified through other sources (pearling, google searches)	1
Total number of records for inclusion[a]	**29**

[a]*Publications identified for inclusion: Annemans et al., 2007; Au et al., 2013; Avenell et al., 2004; Bemelmans et al., 2008; Dalziel & Segal, 2007; Eriksson et al., 2010; Finkelstein et al., 2015; Fuller et al., 2013; Fuller et al., 2014; Galani et al., 2007; Ginsberg & Rosenberg, 2012; Hoerger et al., 2015; Mernagh et al., 2010; Karnon et al., 2013; Lewis et al., 2014; McConnon et al., 2007; McRobbie et al., 2016; Meads et al., 2014; Miners et al., 2012; Roux et al., 2006; Roux et al., 2008; Salkeld et al., 1997; Smith et al., 2016; Trueman et al., 2010; Tsai et al., 2005; Tsai et al., 2013; van Wier et al., 2012; Verhaeghe et al., 2014; Wilson et al., 2015.*

A summary of the cost-utility analyses is provided in Table 2.4. Of the 29 included studies, 19 were conducted since 2010 and the remaining ten prior to 2010. The majority of the CUAs were conducted in Europe; five studies were conducted in Australia. An equal number of studies used a health care funder perspective or a societal perspective. Most behavioural interventions were conducted in a primary care setting.

Table 2.4 Summary of behavioural CUAs for obesity

Author	Country	Perspective	Setting
Salkeld 1997	Australia	Health care payer/societal	Primary care
Avenell 2004	UK	Health care payer	Primary care
Tsai 2005	USA	Societal	Primary care
Roux 2006	USA	Societal	Urban
Annemans 2007	Belgium	Societal	Fitness setting
Dalziel 2007	Australia	Societal	Community
Galani 2007	Switzerland	Societal	Primary care
McConnon 2007	UK	Societal	Primary care
Bemelmans 2008	Netherlands	Health care payer	Primary care
Roux 2008	USA	Societal	Community
Eriksson 2010	Sweden	Societal	Primary care
Mernagh 2010	New Zealand	Health care payer	Community
Trueman 2010	UK	Health care payer	Primary care
Ginsberg 2012	Israel	Societal	Primary care/community
Miners 2012	UK	Health care payer	NR
van Weir 2012	Netherlands	Societal and business	Business setting
Au 2013	UK	Health system	Primary care
Fuller 2013	Australia, UK, Germany	Health care payer/societal	Primary care
Karnon 2013	Australia	Health care payer	Primary care
Tsai 2013	USA	Health care payer	Primary care
Finkelstein 2014	USA	Health care payer	Primary care
Fuller 2014	Australia	Health care payer	Primary care
Lewis 2014	England	Health care payer (NHS)	Community
Meads 2014	UK	Health care payer	Primary care
Verhaeghe 2014	Belgium	Societal	Community
Wilson 2015	USA	Societal	Community
Hoerger 2015	USA	Health care payer	Primary care
McRobbie 2016	UK	Health care payer (NHS)	Primary care
Smith 2016	USA	Health care payer/societal	Primary care

NR: not reported

2.4.1 Key characteristics of the studies

The key characteristics of the studies in terms of the modelling approach used, interventions modelled, time horizon, assumption around weight regain and comorbidities are discussed below.

Interventions modelled

A range of behavioural interventions were modelled, with the most common interventions including diet and exercise or advice/counselling. Four of the studies evaluated commercial weight-loss programs, including programs such as Weight Watchers[11] and Jenny Craig[12] (Meads et al., 2014; Fuller et al., 2013; Finkelstein et al., 2014; Fuller et al., 2014). The

[11] Weight Watchers: https://www.weightwatchers.com/au/
[12] Jenny Craig: https://www.jennycraig.com.au/

counselling interventions consisted of advice provided by either a nurse or GP, behavioural therapy, videos, intensive advice, social support, self-help material, workplace counselling or internet-based interventions. The three studies evaluating internet-based interventions included provision of internet advice with support (McConnon et al., 2007), an interactive e-learning program (Miners et al., 2012) and a web-based lifestyle program (Smith et al., 2015). Ten studies compared multiple interventions with two studies including public health interventions in the comparison (Salkeld et al., 1997; Annemans et al., 2007; Dalziel & Segal, 2007; Bemelmans et al., 2008; Roux et al., 2008; Mernagh et al., 2010; Van Wier et al., 2012; Fuller et al., 2013; Tsai et al., 2013; Lewis et al., 2014). Three studies included community-based interventions consisting of a combination of media campaigns, self-help groups, risk assessment and counselling (Bemelmans et al., 2008; Roux et al., 2008; Wilson et al., 2015). The most common comparators in the models were no intervention or usual care. Table 2.5 summarises the interventions, comparators, model type and the time horizon.

Table 2.5 Design and methods used in behavioural CUAs of obesity

Author	Model type	Horizon	Intervention	Comparator
Salkeld 1997	Trial -based Simulation	Lifetime	GP lifestyle change program, video group, video + self-help group	Routine care
Avenell 2004	Markov	6 years	Low-fat diet and exercise (dietician and supervised)	Oral and written info about diet and exercise
Tsai 2005	Trial-based	One year	Low-carbohydrate diet	Standard diet
Roux 2006	Simulation	Lifetime	Diet, Diet/pharma, Diet/exercise, Diet/exercise/behaviour (6 months)	Routine care
Annemans 2007	Markov	25 years	Physical exercise	No intervention
Dalziel 2007	Markov	20 years	Diet/exercise, advice, counselling, media campaigns, workplace	Controls varied
Galani 2007	Markov	Lifetime	Advice, counselling, consultations with dietician and exercise (3 yrs)	Basic dietary counselling
McConnon 2007	Trial based	One year	Internet: advice/support (12 mnths)	Usual care
Bemelmans 2008	Markov	20-80 years	Community-based approach (90%) and intensive approach (10%)	No intervention
Roux 2008	Markov	Lifetime	Community-wide campaign, social support, enhanced access to PA	No intervention
Eriksson 2010	Trial based	3 years	Supervised exercise sessions, diet counselling and group meetings	Standard care
Mernagh 2010	Simulation	Lifetime	Various public health programmes	No intervention
Trueman 2010	Trial based + simulation	Lifetime	Counterweight, GP weight management advisors (one year)	No intervention
Ginsberg 2012	NR – – budget impact	One year lifetime.	8 interventions: National Prevention and Health Promotion Program	The comparator is unclear
Miners 2012	DES	Lifetime	E-learning device: behavioural changes – diet and exercise patterns	Standard care
van Weir 2012	Trial-based	Two years	Distance lifestyle counselling (telephone and internet)	Self-help

Author	Model type	Horizon	Intervention	Comparator
Au 2013	Markov	Lifetime	Standard behavioural therapy (6 months) meal plans, shopping lists	Standard behavioural therapy
Fuller 2013	Trial based	One year	Weight-loss program by commercial provider (12 months)	Weight-loss program based on standard care
Karnon 2013	Risk adjusted CUA	One year	High level of involvement from the practice nurse	Low involvement from practice nurse
Tsai 2013	Trial-based	Two years	Brief lifestyle counselling; enhanced lifestyle counselling	Usual care
Finkelstein 2014	Regression	5 years	Qsyma and lifestyle (weight watchers etc., Jenny Craig, Vtrim)	Lifestyle (low cost/low intensity intervention)
Fuller 2014	Markov	Lifetime	Weight-loss program by commercial provider (weight watchers) (1 year)	Standard care
Lewis 2014	Simulation	10 years	Very low calorie diet replacement weight-reduction program.	BMI ≥30:weight watchers BMI ≥ 40: gastric banding
Meads 2014	Markov	Lifetime	Referral to commercial weight-loss program (12 weeks)	Usual care i.e., no active component
Verhaeghe 2014	Markov	Lifetime	Health promotion of physical activity and healthy eating (10 wks)	Usual care
Wilson 2015	Archimedes^ simulation	20 years	12 week community based weight control program	Usual care
Hoerger 2015	Markov	Lifetime	Medicare Intensive Behavioural program (6 months)	Usual care
McRobbie 2016	Trial based	One year	Weight Action Programme (WAP)	Nurse led intervention
Smith 2016	Markov	10 years	Online adaptation of the diabetes prevention program(ODPP) (one yr)	Usual care

NR: Not reported, DES: Discrete Event Simulation, Simulation models use risk equations for comorbidities modelling patients alongside a trial., ^The Archimedes Outcomes Analyzer (modelling program) projected lifetime health outcomes and costs.

Time Horizon

The time horizon of the models ranged from one year to a lifetime horizon. The majority of studies used a time horizon of 20 years or more (up to a lifetime) (Salkeld et al., 1997; Roux et al., 2006; Annemans et al., 2007; Dalziel & Segal, 2007; Galani et al., 2007; Bemelmans et al., 2008; Roux et al., 2008; HTA et al., 2010; Trueman et al., 2010; Miners et al., 2012; Au et al., 2013; Fuller et al., 2014; Meads et al., 2014; Verhaeghe et al., 2014; Wilson et al., 2015; Hoerger et al., 2015). Eight studies used short-term time horizons between one and three years (Tsai et al., 2005; McConnon et al., 2007; Eriksson et al., 2010; van Weir et al., 2012; Fuller et al., 2013; Karnon et al., 2013; Tsai et al., 2013; McRobbie et al., 2016). The time horizon used in one study (Ginsberg & Rosenberg, 2012), was not clearly stated.

Model type

Seven studies conducted an economic evaluation alongside a trial (Tsai et al., 2005; McConnon et al., 2007; Eriksson et al., 2010; van Weir et al., 2012; Fuller et al., 2013; Tsai et al., 2013;

McRobbie et al., 2016). All of these seven only conducted a cost-utility analysis for the length of the trial (ranging from one to three years) and none extrapolated results past the trial period. Most studies used decision analytic models, such as Markov or simulation modelling (Salkeld et al., 1997; Avenell et al., 2004; Roux et al., 2006; Annemans et al., 2007; Dalziel & Segal., 2007; Galani et al., 2007; Bemelmans et al., 2008; Roux et al., 2008; HTA et al., 2010; Trueman et al., 2010; Miners et al., 2012; Au et al., 2013; Karnon et al., 2013; Finkelstein et al., 2014; Fuller et al., 2014; Lewis et al., 2014; Meads et al., 2014; Verhaeghe et al., 2014; Wilson et al., 2015; Hoerger et al., 2015; Smith et al., 2016).

Of those studies that extrapolated outcomes into the future, 12 used Markov models (Avenell et al., 2004; Annemans et al., 2007; Dalziel & Segal, 2007; Galani et al., 2007; Bemelmans et al., 2008; Roux et al., 2008; Au et al., 2013; Fuller et al., 2014; Meads et al., 2014; Verhaeghe et al., 2014; Hoerger et al., 2015; Smith et al., 2016), and five used micro-simulation models (Roux et al., 2006; Mernagh et al., 2010; Trueman et al., 2010; Miners et al., 2012; Wilson et al., 2015).

In the studies that used simulations, the annual risks of comorbidities were informed by equations such as those derived from the Framingham Heart Study[13] or QRISK2, where the risk of CVD events is higher in individuals with a higher BMI (Salkeld et al., 1997; Miners et al., 2012). Micro-simulation models used risk equations to estimate transition probabilities to states of obesity-related comorbidities (such as diabetes, cancer heart disease) to simulate obese patients over time (Lewis et al., 2014; Trueman et al., 2010; Mernagh et al., 2010).

Other modelling methods included regression modelling to extrapolate results over five years (Finkelstein et al., 2014) and a simulation program (Archimedes Outcomes Analyzer) to project lifetime health outcomes and costs (Wilson et al., 2015). Figure 2.6 displays the breakdown of the key characteristics of the studies included in the review.

[13]Framingham Heart Study: https://www.framinghamheartstudy.org/
QRISK2: https://qrisk.org/

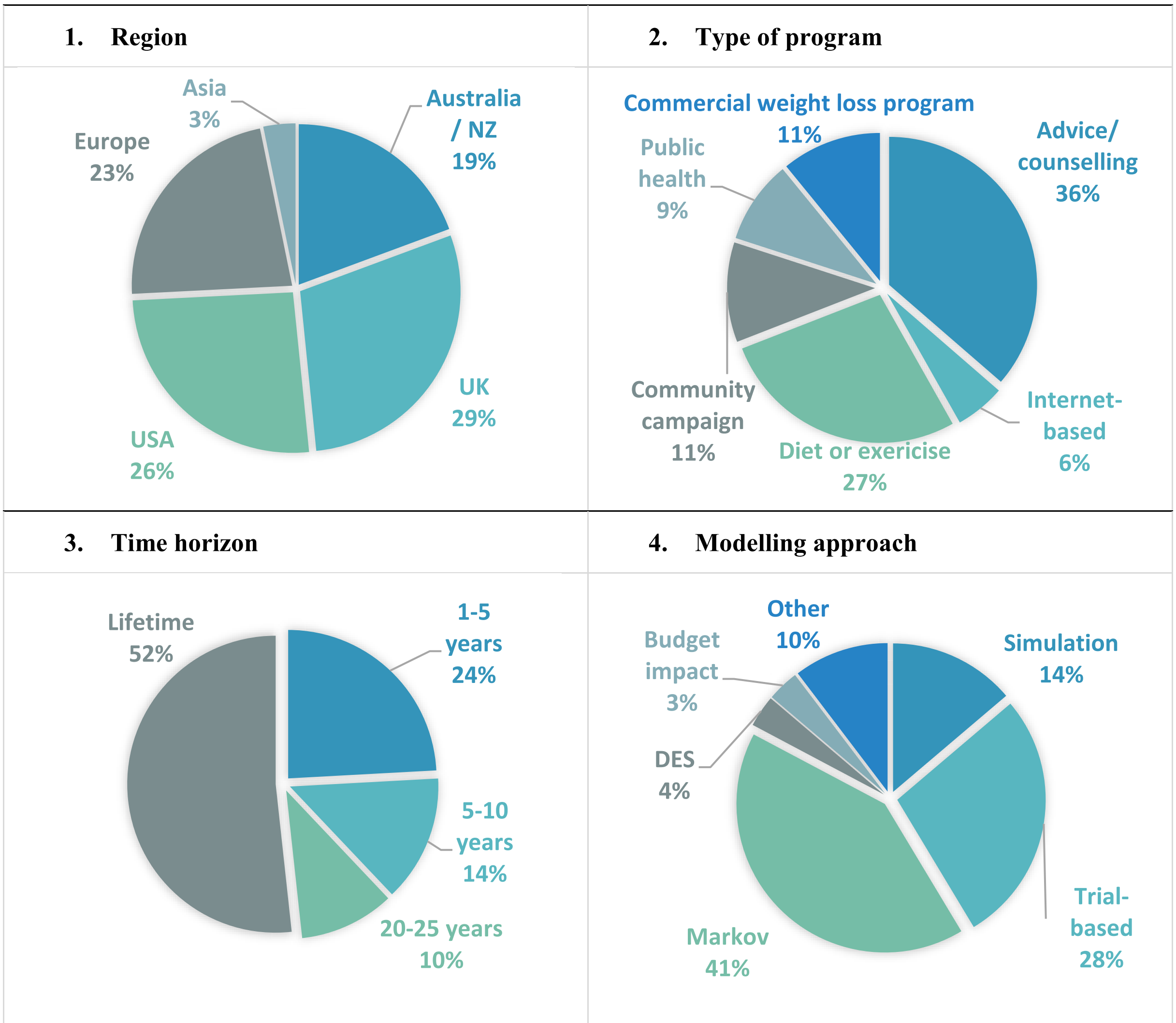


Figure 2.6 Key characteristic of behavioural cost-utility analyses for obesity

Weight maintenance and regain

A particularly relevant issue when modelling obesity interventions is the extent to which any weight-loss is maintained or regained. Assumptions relating to weight changes are highly influential in terms of the results of a cost-effectiveness analysis. The NICE health guidelines for weight management report that cost-effectiveness is highly sensitive to modelling inputs around regaining weight and provided recommendations on using weight re-gain in economic evaluations of pharmaceutical interventions (Neovius & Narbro, 2008).

Eighteen studies attributed weight loss due to the intervention beyond a time horizon of more than two years (Roux et al., 2006; Annemans et al., 2007; Galani et al., 2007; Bemelmans et al., 2008; Roux et al., 2008; HTA et al., 2010; Trueman et al., 2010; Ginsberg, 2012; Miners et al., 2012; Au et al., 2013; Finkelstein et al., 2014; Fuller et al., 2014; Lewis et al., 2014; Meads et al., 2014; Verhaeghe et al., 2014; Wilson et al., 2015; Hoerger et al., 2015; Smith et al., 2016).

Assumptions pertaining to weight gain and waning of the effectiveness varied considerably across the studies. Eights studies assumed weight would be regained (Roux et al., 2006; Galani et al., 2007; Trueman et al., 2010; Miners et al., 2012; Au et al., 2013; Lewis et al., 2014; Meads et al., 2014; Hoerger et al., 2015). Three studies included a decline in effectiveness in the intervention over time (Roux et al., 2008; Mernagh et al., 2010; Finkelstein et al., 2014).

Six studies did not include assumptions or clearly articulate that weight would be regained post intervention (Annemans et al., 2007; Bemelmans et al., 2008; Ginsberg et al., 2012; Fuller et al., 2014; Wilson et al., 2015; Smith et al., 2016). This is a concern given weight changes and effectiveness over time are instrumental assumptions that drive the ICERs.

Furthermore, the assumptions concerning weight loss were not always suitably tested or presented in sensitivity analyses (Galani et al., 2007; Bemelmans et al., 2008; Ginsberg et al., 2012; Au et al., 2013; Fuller et al., 2013; Fuller et al., 2014; Lewis et al., 2014; Meads et al., 2014; Horerger et al., 2015). Seven studies did test assumptions concerning weight loss (Roux et al., 2006; Roux et al., 2008; Mernagh et al., 2010; Trueman et al., 2010; Miners et al., 2012; Finkelstein et al., 2014; Verhaeghe et al., 2014; Wilson et al., 2015) despite the fact that most studies found that results of the analysis were sensitive to effectiveness of the weight-loss interventions.

Comorbidities modelled

A number of the studies modelled the effect of weight gain on comorbidities, such as cardiovascular disease, Type 2 diabetes, stroke and cancer (Salkeld et al., 1997; Avenell et al., 2004; Roux et al., 2006; Annemans et al., 2007; Galani et al., 2007; Bemelmans et al., 2008; Roux et al., 2008; HTA et al., 2010; Trueman et al., 2010; Miners et al., 2012; Au et al., 2013; Karnon et al., 2013; Fuller et al., 2014; Lewis et al., 2014; Meads et al., 2014; Verhaeghe et al., 2014; Hoerger et al., 2015; McRobbie et al., 2016; Smith et al., 2016).

Seven studies did not include obesity related comorbidities in their models (Tsai et al., 2005; McConnon et al., 2007; Ginsberg et al., 2012; van Weir et al., 2012; Fuller et al., 2013; Tsai et al., 2013; Finkelstein et al., 2014). Five studies did not model changes in weight or BMI;

instead, they modelled changes in QoL and obesity-related conditions (Salkeld et al., 1997; Avenell et al., 2004; Dalziel & Segal, 2007; Eriksson et al., 2010; McRobbie et al., 2016). The choice not to explicitly model changes in weight was rationalised on the grounds that weight loss would reduce the risk of comorbidities (Avernell et al., 2004; Eriksson et al., 2010).

Changes in weight are intermediate outcomes, whereas changes in life expectancy and QoL are patient-relevant outcomes and, as such, more acceptable to decision makers. However, a major inaccuracy in these models is that they assume that weight loss will reduce the risk of comorbidities to that of normal-weight individuals. Realistically, an individual who has been obese for a significant period will still have an increased risk of comorbidities compared to normal-weight individuals. The Markov models incorporating obesity-related conditions as separate health states assume that an individual cannot have multiple coexisting comorbidities, which limits how these analyses can be interpreted (Annemans et al., 2007; Galani et al., 2007; Au et al., 2013; Verhaeghe et al., 2014).

2.4.2 Utility values modelled

The utility values used in the models differed in terms of how the values were applied and the sources of the utility values. Table 2.6 summarises the utility weights used in the analyses, the source of these values and the resulting ICER for each intervention studied. A quality score[14] sourced from the Tufts CEA registry is also provided.

[14] The CEA registry includes a quality score of included economic evaluations. The score is between 1 (lowest quality) and 7 (highest quality). The scores are based on an assessment authors reporting ICERs, sensitivity analysis, correctly used health economic assumptions (discount rate, currency, time) and appropriately estimated utility weights.
http://healtheconomics.tuftsmedicalcenter.org/cear4/SearchingtheCEARegistry/Definitions.aspx

Table 2.6 Utility values and ICERs reported in cost-utility analyses

Author	Quality Score (out of 7)	Utility weight	Value	Source	Type of utility score	ICER ($US 2015)/QALY
Annemans 2007	4.5	Male with Type 2 diabetes	0.689	Coffey 2002	QWB index	$3,700 $22,000 $15,000 (3 age groups)
		BMI disutility (per unit)	-0.021	Warren 2004	SF-36 (trial)	
		Disutility female	-0.038	Karnon 2003	Breast cancer patients	
		TIA (decrement)	-0.044	Currie 2005	EQ-5D, SF-36	
		Stroke (decrement)	-0.072			
		CVD (decrement)	-0.052			
Au 2013	5	BMI normal (males)	0.910	Kinge 2010	EQ-5D (UK norms)	$280 (grocery list vs none) Cost-saving (grocery list vs. standard therapy)
		BMI normal (females	0.904			
		BMI overweight (males)	0.897	Jia 2005	SF-12/EQ-5D (norms)	
		BMI overweight (females)	0.891			
		BMI obese (males)	0.877	Sach 2007	VAS, EQ-5D, SF-6D	
		BMI obese (females)	0.871			
Avenell 2004	N/A	Diabetes	0.90	Harvard CUA database	NA	$25,818
		No diabetes	0.96	Clegg (2002)	Assumption	
Bemelmans 2008	3	By disease state	NR	Mathers 2001, Stouthard 1997	Life expectancy and disability weights	$12,000 (lifestyle) $7,800 (community $8,900 (combined)
Dalziel 2007	4	Normal weight (BMI model)	0.85	McNeil and Segal, 1999	AQoL	$11,000 (Nurse checks)
		Obese (BMI model)	0.78			
		Overweight (BMI model)	0.82			
Eriksson 2010	5.5	Adult patients with hypertension, T2DM, dyslipidemia, obesity or any combo	0.70	In trial	SF-36	Cost-saving
Finkelstein 2014	5	Obesity placebo group	0.797	In trial	SF-12	$35,000 (weight watchers)
		Obesity treatment with Qsymia	0.803			
Fuller 2014	6	Normal state	0.81	In trial	IWQOL-lite	$12,000
		Overweight state	0.81			
		Obese state	0.78			
		T2DM	0.75			

Author	Quality Score (out of 7)	Utility weight	Value	Source	Type of utility score	ICER ($US 2015)/QALY
Fuller 2013	3.5	Improvement in utility score from weight loss (2 arms comparison)	0.015-UK 0.021-AUS 0.009-GER	In trial	IWQOL-lite	$13,000 (UK) $19,000 (Australia) $43,000 (Germany)
Galani 2008	N/A	Utility by BMI/age	age/BMI	Macran 2004	EQ-5D (UK norms)	All ICERs below $2,127
		Utility gain due to 1 unit decrease in BMI	age/BMI	Hakim 2002	VAS (obese)	
		Disutility due to obesity complications	age/BMI	Jia 2005	SF-12/EQ-5D (norms)	
Ginsberg 2012	3.5	BMI 20 or less, underweight	0.741	Tsai 2005	SF-36	$14,000 (office based vs none)
		BMI 20-24.9	0.787			
		BMI 25-29.9	0.769			
		BMI 30-34.9	0.672			
		BMI $\geq$ 40	0.624			
Hoerger 2015	5	Decrement for being obese	-0.007	Ackermann 2009	SF-36 (overweight)	Cost-saving
Mernagh 2010	N/A	Back problems	0.81	Mittman 1999	HUI-3 (patients)	$6,179 (general health screening) $133,878 (Green prescription)
		Cancer	0.82			
		Diabetes	0.79			
		Heart disease	0.77			
		Stroke	0.68			
		Hip osteoarthritis	0.48			
		Knee osteoarthritis	0.71	Grinrod 2010	HUI-3 (patients)	
Karnon 2013	3	QALY gain per one point decrease in BMI	0.055	Trueman 2010	Marcran (EQ-5D)	$6,700
Lewis 2014	N/A	BMI 18.35	0.86	Macran 2004	EQ-5D (UK population norms)	$20,105 $21,048 $21,271 $20,677
		BMI 23	0.87			
		BMI 28	0.84			
		BMI 35	0.80			
		BMI 40	0.78			
McConnon 2007	5	Mean QALY change	Per respondent	In trial	EQ-5D	$87,000
Mc Robbie 2016	N/A	Difference between 2 arms of trial	0.015	In trial	EQ-5D-5L	$12,325
Meads 2014	5.5	Decrement by age	Various	Maheswaran 2013	EQ-5D	Cost-savings
		Decrement BMI <25	0			
		Decrement BMI 25-29.9	-0.006			
		Decrement BMI 30-34.9	-0.033			
		Decrement BMI 35-39.9	-0.033			

Author	Quality Score (out of 7)	Utility weight	Value	Source	Type of utility score	ICER ($US 2015)/QALY
		Decrement BMI ≥ 40	-0.117			
		Decrement Type 2 diabetes	-0.096			
		Decrement Stroke 1 year	-0.16			
		Decrement Stroke ≥year 2	-0.080			
		Decrement MI year 1	-0.139			
		Decrement MI year 2	-0.070			
Miners 2012	5.5	NR	NR	Macran 2004	EQ-5D (UK norms)	$176,400
Roux 2008	5.5	By disease state (cancer, CHD, stroke, Type 2 diabetes, activity level)	NR	Tengs 2003 Kaplan 2001	QWB	$18,000 $37,000 $37,000 $38,000 $51,000 $60,000 $88,000
Roux 2006	5	Obesity	0.87	Estimated from sample of women	Assumption	$17,000
		Obesity after 10% weight loss	0.93			
		T2DM	0.75	Beaver Dam Outcome Study	Fryback (1993) SF-36 (cohort)	
		CHD	0.75			
Salkeld 1997	5.5	Angina	0.90	Glasziou 1994	TTO (after CHD event)	Most dominated $180,000 $35,000 (video vs routine care)
		Coronary insufficiency	0.90			
		MI	0.90			
		Stroke	0.76			
		Unrecognised MI	0.95			
Smith 2016	N/A	No diabetes	0.880	Herman 2005	QWB (patients pre-diabetes)	$15,599
		Stable diabetes	0.689			
		Complicated diabetes	0.593			
Trueman 2010	4.5	Female BMI < 21	0.85	Macran 2004 (*values were not significant for men)	EQ-5D (UK population norms)	Cost-saving
		Female BMI 21-25	0.87			
		Female BMI 26-30	0.82			
		Female BMI 30-39	0.78			
		Female BMI > 39	0.78			
		Male BMI < 21	0.86			

Author	Quality Score (out of 7)	Utility weight	Value	Source	Type of utility score	ICER ($US 2015)/QALY
		Male BMI 21-25	0.87			
		Male BMI 26-30	0.86			
		Male BMI 30-39	0.82			
		Male BMI > 39	0.88			
Tsai 2005	5	Difference in QALYs between two groups	NR	In trial	SF-36	Cost-saving
Tsai 2013	4	Usual care	0.72	In trial	EQ-5D	$120,000 (enhanced vs usual care) $40,000 (enhanced vs brief) Dominated (brief vs usual care)
		Brief lifestyle counselling	0.78			
		Enhanced brief lifestyle counselling	0.77			
Van Wier 2012	6	AUC utility - control group	0.908	In trial	EQ-5D	$21,000 (phone vs control) $550,000 (internet vs. control)
		AUC utility - phone group	0.917			
		AUC utility – internet group	0.915			
Verhaeghe 2014	5.5	At risk of T2DM, heart disease, stroke/colon cancer	0.71	Saami 2010	EQ-5D (mental health patients)	$33,000 (male)
		Colon cancer after 1 year	0.64	De Smedt 2012	Secondary souces	$39,000 (female)
		Colon cancer within 1	0.64			
		Coronary heart disease > year	0.56			
		Coronary heart disease 1 year	0.47			
		Patients with stroke 1	0.50			
		Patients with T2DM	0.63			
		Stroke within 1 year of	0.50			
Wilson 2015	N/A	Mean utility by ICD-9 score	range	Sullivan 2006	EQ-5D	$57,430
		Type 2 diabetes – men	0.69	Coffey 2002	QWB index	
		Type 2 diabetes – women	0.65			
		Type 1 diabetes – men	0.67			
		Type 1 diabetes – women	0.64			

N/A = not available, NR = not reported

Eight studies applied utility values based on BMI, (Dalziel & Segal, 2007; Galani et al., 2008; Trueman et al., 2010; Ginsberg & Rosenberg, 2012; Miners et al., 2012; Au et al., 2003; Karnon et al., 2013; Lewis et al., 2014), five studies applied utility values by BMI and disease state (Roux et al., 2006; Annemans et al., 2007; Eriksson et al., 2010; Meads et al., 2014, Hoerger et al., 2015) eight studies applied utility values based only on disease state (such as diabetes, cancer, heart disease, stroke) (Salkeld et al., 1997; Avenell et al., 2004; Bemelmans et al., 2008; Roux et al., 2008; Mernagh, 2010; Verhaeghe et al., 2014; Smith et al., 2016) and eight studies applied utility values collected within-trial (Tsai et al., 2005; McConnon et al., 2007; Van Wier et al., 2012; Fuller et al., 2013; Tsai et al., 2013; Finkelstein et al., 2014; Fuller et al., 2014; McRobbie et al. 2016). The trials collecting QoL data used the SF-36 (N=1), EQ-5D (N=4) and the IWOQOL-lite (N=2) and the SF-12(N=1).

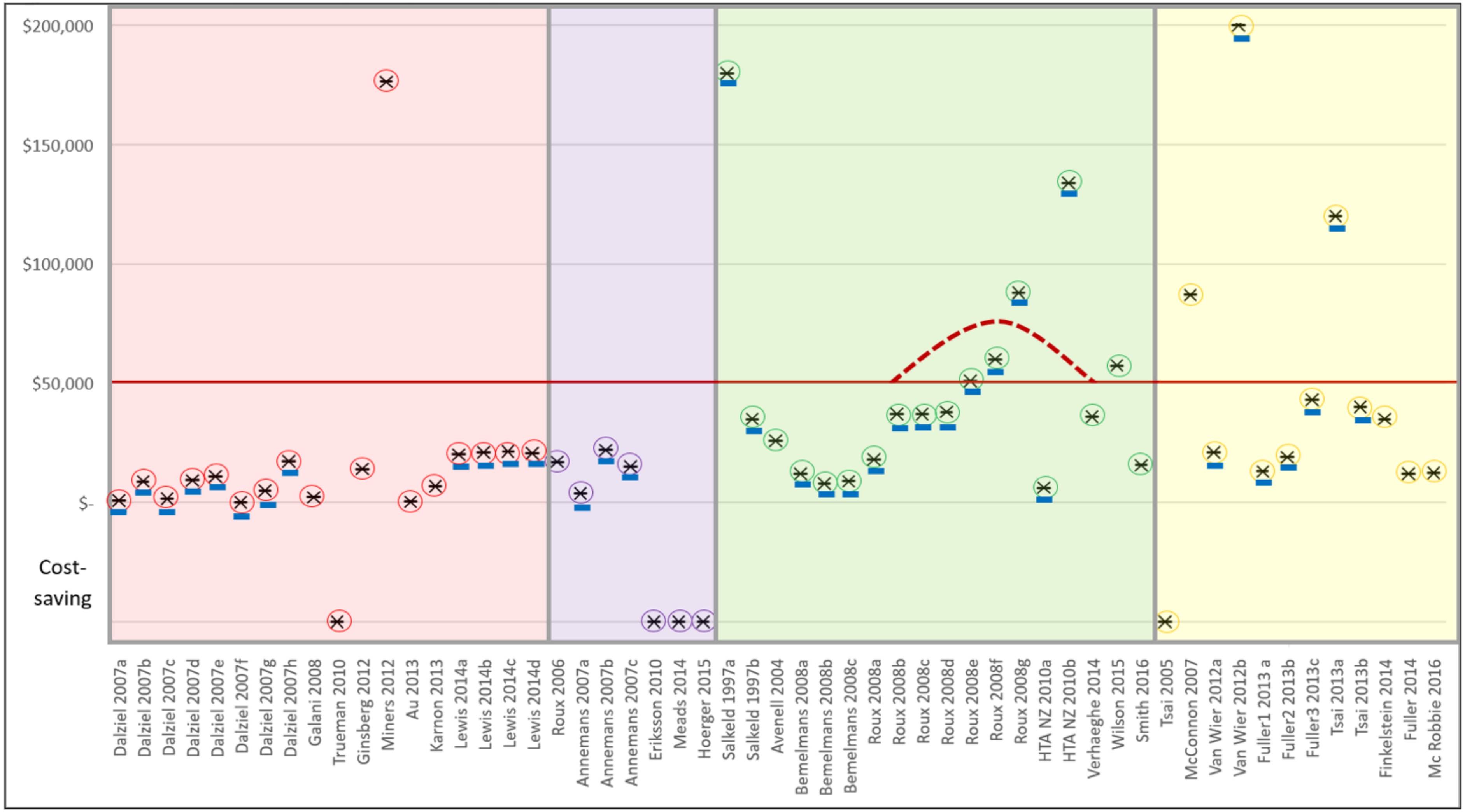
Of those studies that applied utility values by BMI, some applied a per unit reduction in BMI (Annemans et al., 2007; Karnon et al., 2013; Hoerger et al., 2015; Galani et al., 2008), whilst others used population norms sourced from Macran (2004) (Galani et al., 2007; Trueman et al., 2010; Miners et al., 2012; Lewis et al., 2014) and one study used QoL values based on a study using AQoL (Dalziel & Segal, 2007). Macran (2004) was a UK study that explored the relationship between BMI and QoL and published cross-sectional utility values based on the EQ-5D, by age, sex and BMI category. This study was used as the source of utility values in four of the analyses (Galani et al. (2008), Miners et al. (2012), Trueman et al. (2010), Lewis et al. (2015). One issue with using population norms is that those who lose weight (and return to normal weight) are assumed to have the same QoL as someone who remained in a normal weight category, which may be overstating the QoL gains associated with weight loss. Furthermore, the EQ-5D weighted index scores reported in Macran (2004) were not statistically significant for males across certain age categories, indicating a possible erroneous application of these values in the models.

The studies that based the utility value on the per unit reduction in BMI ranged from –0.021 (Annemans et al., 2007), to –0.007 (Hoerger et al., 2015) and 0.017 (Galani et al., 2007) per unit decrease in BMI One study applied a gain in utility of 0.055 per unit of BMI lost (Karnon et al., 2013). A criticism of using a per unit reduction in BMI is that this assumes a linear decrease in QoL across all BMI groups in terms of a change in kilograms. A one-unit decrease in BMI over a one-year period that increases utility does not automatically assume the reverse is true, i.e., that a one-unit increase in BMI results in the equivalent decrease in utility. Other studies did not provide sufficient referencing of their data sources to verify the utility values or the values stated did not match the source reference (Miners et al., 2012; Bemelmans et al., 2008; Galani et al., 2008; Ginsberg & Rosenberg, 2012). For example, Ginsberg and Rosenberg (2012) sourced a trial (Tsai et al., 2005) for the utility values; however, after inspection of this paper, it is unclear how they derived these values from the data reported in the study. Overall, a multitude of measures were used to assess QoL, with the EQ-5D and SF-36 most commonly used. The majority of studies used utility values sourced from published literature, which may not accurately reflect the population being modelled, as many studies did not provide adequate details of how utility values were applied in the models. The methodology used, and application of utility values differed for each model presented thus reducing the ability make comparative judgements on which interventions provide the best gains in QoL. These methodological differences also hider the ability to compare overall model outcomes.

2.4.3 Cost-effectiveness results

All the studies included in the review reported the results of cost-effectiveness as the cost per QALY gained. To compare the results across studies, all the ICERs were converted to a common year and currency (2015 US$). All reported ICERs from countries outside the US were converted to US dollars using exchange rates based on the reported year for costs, then US costs were inflated to the year 2015. Figure 2.7 displays the ICERs from all the interventions evaluated within the cost-utility analyses. The red line on the graph represents a willingness-to-pay threshold of $50,000 per QALY (with the dashed red line representing interventions that would have been considered cost-effective in the year the study was conducted). All ICERs below the red line are considered cost-effective (at a $50,000 per QALY threshold). The interventions shaded red denote utility values by BMI state, purple denotes utility values by BMI and disease state, green denotes utility by disease state and yellow denotes QoL values collected within a trial. The blue line under the ICER represents interventions that were part of a multi-intervention comparison within one study.

Of the 55 interventions assessed in the cost-effectiveness analyses, all but ten would be considered cost-effective at $50,000 per QALY gained, with five of the interventions considered cost-saving (Tsai et al., 2005; Eriksson et al., 2010; Trueman et al., 2010; Meads et al., 2014; Hoerger et al., 2015). The interventions with the lowest ICERs (i.e., the most cost-effective) were reported in those studies that implemented utility values by BMI states. Only one study using QoL by BMI state or in combination with disease-state utilities (Miners et al. 2012) reported an ICER of $176,400, in relation to an e-learning intervention. The results from another study of an internet-based intervention (McConnon et al., 2007) similarly found the intervention not to be cost-effective (ICER = $87,000). Those studies that were conducted alongside a trial reported the highest ICERs compared to the other studies; however the majority of these studies were still considered cost-effective (nine out of 12).



Note: ▬ *studies from multi-intervention comparisons,* ◯ *studies with utility by BMI,* ◯ *studies with utility by BMI and disease states,* ◯ *indicates studies with utility by disease state and* ◯ *studies that applied utility collected in a trial,* ---- *indicates studies that would have been considered cost-effective in the year of the study*

Figure 2.7 Cost utility results by study (cost per QALY)

Interestingly, interventions were more likely to be deemed cost-effective if they were evaluated alone as, opposed to a multi-intervention evaluation. The five studies that found cost-saving interventions were all based on evaluations of one intervention compared to usual care or no intervention. Seven out of the ten interventions that were not deemed cost-effective were part of a multi-intervention comparison. This highlights the difficulty in comparing multiple studies to identify which interventions would be considered best 'value for money'. Moreover, increasing the willingness to pay threshold further reinforces the finding that most obesity interventions assessed are deemed cost-effective. An implication of assessing the cost-effectiveness of multi-interventions in a single model is that many of the interventions are considered cost-effective relative to no intervention, but not cost-effective relative to the next-best alternative in the model. The evaluations of single interventions that resulted in ICERs not considered cost-effective (Miners et al., 2004, McConnon et al., 2007, Wilson et al., 2015), was attributed to high fixed costs associated with set up of the intervention, combined with a negligible impact on QoL. Overall, all the interventions based on diet or exercise were considered cost-effective and those with the highest ICERs were a combination of community programs, counselling and internet-based interventions.

2.5 Summary of the systematic reviews of non-behavioural interventions for obesity

As mentioned previously, this chapter is specifically interested in the economic evaluations of behavioural interventions. Therefore, only a summary of the systematic reviews of pharmacological and surgical interventions used for the treatment of obesity will be discussed. These studies are discussed to gain an overall picture of the modelling methods used to evaluate obesity interventions.

2.5.1 Pharmaceutical cost-effectiveness

The three pharmaceutical interventions most commonly studied were orlistat, sibutramine and rimonabant. Of these, orlistat is the only drug currently available under the Australian Pharmaceutical Benefits Scheme (PBS) for reimbursement for weight loss (PBS, 2018). The other two interventions were withdrawn from the market due to safety concerns. Sibutramine was withdrawn from the market in 2010 due to concerns over increased risk of heart attack and stroke (TGA, 2010). Rimonabant was withdrawn from the market in 2009 due to safety concerns over psychiatric effects (EMA, 2009).

Six publications reviewed the cost-effectiveness of pharmaceutical interventions in individuals with obesity (Ara et al., 2012; Avenell et al., 2004; Boyers et al., 2015; Griffiths et al., 2012; Neovius & Narbro, 2008; Schwander et al., 2016). Two publications, Ara et al. (2012) and Neovius and Narbro (2008), focused solely on pharmaceutical interventions. One of these publications, Ara et al. (2012) included a systematic review of cost-effectiveness analyses of pharmaceutical interventions and an independent economic evaluation of orlistat, sibutramine and rimonabant; however, no reason was provided as to why a new evaluation was not conducted given the change in available pharmaceutical treatments. The authors did acknowledge the withdrawal of the two pharmaceutical treatments during the study. Four publications (Avenell et al., 2004; Boyers et al., 2015; Griffiths et al., 2012; Schwander et al., 2016) reviewed cost-effective analyses of pharmaceutical interventions in addition to other types of interventions, such as surgical and lifestyle interventions. Schwander et al. (2016) identified 87 publications and used descriptive statistics to review the methods used in economic evaluations of treatments in people with obesity. Although, they did not critically appraise the modelling methods used in the studies, the review is useful as an overview of modelling methods using descriptive statistics used in economic evaluations.

The cost-effectiveness analyses identified in the systematic literature reviews generally overlapped (Table 2.7), and only a few studies were not common to the reviews, as the criteria for each systematic review differed slightly and were conducted in different years.

Table 2.7 Economic evaluations identified in published systematic reviews of pharmaceutical interventions

	Avernell et al. 2004	Neovius & Narbro 2008	Ara et al. 2012	Griffith et al. 2012	Boyers et al. 2015	Schwander et al. 2016
Foxcroft 1999	✓	✓	✗	✗	✗	✗
Pharma/Knoll 2000	✓	✗	✗	✗	✗	✗
Lamotte 2002	✓	✓	✓	✓	✗	✓
Maetzel 2003	✗	✓	✓	✓	✓	✓
Warren 2004	✗	✓	✓	✓	✗	✓
Foxcroft 2005	✗	✓	✓	✓	✗	✗
Hertzman 2005	✗	✓	✓	✓	✗	✓
Lacey 2005	✗	✓	✓	✓	✗	✓
Malone 2005	✗	✓	✗	✓	✗	✗
Ruof 2005	✗	✓	✓	✗	✗	✓
Brennan 2006	✗	✓	✓	✗	✗	✓
Brown 2006	✗	✗	✓	✗	✗	✓
Roux 2006	✗	✗	✓	✗	✗	✓
van Baal 2008	✗	✓	✓	✓	✗	✓
Ara 2007	✗	✓	✓	✗	✗	✓
Caro 2007	✗	✓	✗	✓	✗	✓
Hampp 2008	✗	✓	✓	✓	✗	✓
Iannazzo 2008	✗	✓	✓	✓	✓	✓
Burch 2009	✗	✗	✓	✗	✗	✓

The systematic reviews assessing only pharmaceutical treatments reached similar conclusions (Ara et al., 2012; Neovius & Narbro, 2008). These reviews concluded that the published economic evaluations supported adoption of pharmaceutical interventions. However, criticisms of the evaluations conducted were made concerning:

- assumptions of weight maintenance and regain (Ara et al. 2012; Neovius & Narbro, 2008). The results of the published cost-effectiveness analyses were sensitive to assumptions pertaining to changes in weight. Extrapolation of the benefits accrued over time diverged considerably and favoured the intervention arms.

- trial drop-out rates. The results were sensitive to attrition in the clinical trials, which tended to have high drop-out rates. The analytical models used effectiveness estimates based on subjects completing the trials. For this reason, the results may understate ICERs presented (Ara et al., 2012, Neovius & Narbro, 2008).

- extrapolation of potential benefits accrued from drug therapy, such as changes in QoL and utility (Ara et al., 2012; Avernell et al., 2004; Neovius & Narbro, 2008) and improvements in obesity related comorbidities (Boyers et al., 2015)). Chronic health-related conditions are associated with obesity. Often utility and QoL values would be coupled with changes in weight, BMI or comorbidities representing health states modelled.

- Utility per kilogram lost was a key driver of the results. Most studies modelled the relationship between BMI and QoL applying a disutility ranging from 0.014 to 0.0264 per change in BMI unit. Other economic evaluations (N=5) applied disutility values derived by pooling data from clinical trials of patients with obesity treated with orlistat or placebo. Scores were converted from a visual analogue scale (VAS) into time trade-off (TTO) values. A difference of 0.017 in utility was applied for a one-unit change in BMI (Hakim et al., 2002). The oldest study used a utility gain of 0.181 per year for responders losing more than 10% of body weight, which was based on expert opinion (Foxcroft & Milne, 2000).

- Adverse effects were not generally incorporated in the economic models (Neovius & Narbro, 2008). Given that two of the treatments were withdrawn from the market, exclusion of adverse effects favours drug therapy.

A major limitation of the studies was the lack of details regarding the QoL instruments used, the baseline utility weight applied and the modelling techniques for QoL (Ara et al., 2012; Neovius & Narbro, 2008). Overall, the reviews indicate that pharmaceutical obesity treatments may provide good value given the cost of the intervention; however, the methodological limitations of the evaluations reduced the certainty and acceptability of the results (Ara et al., 2012; Avenell et al., 2004; Boyers et al., 2015; Griffiths et al., 2012; Neovius & Narbro, 2008; Schwander et al., 2016). Interestingly, studies not funded by the manufacturing company generally produced results indicating that the pharmaceuticals were not cost-effective given current thresholds (Foxcroft & Ludders, 1999; van Baal et al., 2008; Hampp et al., 2008). All evaluations funded by manufacturing companies had very low ICERs, indicating interventions were cost-effective.

2.5.2 Surgical cost-effectiveness

Seven publications reviewed the cost-effectiveness of surgical interventions in obese individuals (Clegg et al., 2002; Salem et al., 2005; Picot et al., 2009; Terranova et al., 2012;

Avenell et al., 2004; Griffiths et al., 2012; Schwander et al., 2016). Four systematic reviews of CUA assessing surgical interventions were identified (Clegg et al., 2003; Salem et al., 2005; Picot et al., 2009; Terranova et al., 2012). Surgical interventions are normally only considered for patients who are severely obese (BMI ≥ 35 kg/m^2) with comorbidities or for those deemed morbidly obese (BMI ≥ 35 or 40 kg/m^2) (Australian Family Physician, 2013). A range of surgical interventions were assessed, including open gastric bypass, laparascopic gastric bypass, vertical banded gastroplasty, laparascopic adjustable banding, biliopancreatic diversion and duodenal switch.

The cost-effectiveness analyses identified in the systematic literature reviews contained common studies assessing surgical interventions (Table 2.8), except for the systematic review by Schwander et al. (2016), which was conducted much later than the other reviews and consequently included more studies.

Table 2.8 Economic evaluations identified in systematic reviews of surgical interventions

	Clegg et al. 2003[a]	Avernell et al. 2004	Salem et al. 2005	Picot et al. 2009	Griffith et al. 2012	Terranova et al. 2012	Schwander et al. 2016
Chua 1995	✓	✓					
Martin 1995	✓	✓					
Sjostrom 1955	✓	✓					
Segal 1998		✓					
van Gemert 1999	✓	✓	✓		✓		
Nguyen 2001		✓					
Craig and Tseng 2002			✓	✓	✓		✓
Clegg 2003[a]		✓	✓		✓	✓	✓
Jensen and Flum 2005				✓	✓		✓
Ackroyd 2006				✓	✓	✓	✓
van Mastrigt 2006				✓	✓		
Salem 2008				✓	✓	✓	✓
Anselmino 2009						✓	✓
Ikramuddin 2009					✓		✓
Keating 2009					✓	✓	
Picot 2009							✓
Campbell 2010					✓	✓	✓
McEwen 2010					✓		
Hoerger 2010					✓		
Chang 2011							✓
Malkin 2011							✓
Benarroch-Gampel 2012							✓
Picot 2012							✓
Faria 2013							✓
Lee 2013							✓
Pollack 2013							✓
Song 2013							✓
Castilla 2014							✓
Wang 2014							✓
Borisenko 2015							✓

[a] *Clegg 2003 was a systematic review of CUAs and presented an independent CUA.*

Overall, the systematic reviews found that the published CUAs favoured surgical interventions compared to non-surgical treatments but noted the considerable variation in the estimated costs and benefits claimed (Picot et al., 2009). However, not all systematic reviews included critiques of the methodology used in individual economic evaluations. Salem et al. (2005) concluded that bariatric surgery is worth the costs, despite the lack of assessment of the assumptions used in the models. For example, Picot et al. (2009) concluded that a reduction in BMI is associated with gains in utility, but there were doubts surrounding the magnitude of the gain claimed. Terranova et al. (2012) reported that all evaluations found bariatric surgery was cost-effective compared with non-surgical treatments and claimed that surgery was affordable. However, the authors did not critique the assumptions pertaining to QoL inputs in the models or discuss the long-term effects of the surgical procedures

2.5.3 Public policy interventions

There is a paucity of literature concerning the economic evaluation of obesity-related public policy or environmental interventions. One systematic review by McKinnon et al. (2016) reviewed public and environmental policies in the US. In the 27 included studies, interventions included community, environment, nutrition-related policy/education changes, school environments and social marketing/media interventions. All but two of the included studies concluded that the interventions were economically beneficial. Of these, 18 used a cost-effectiveness analysis. The studies that reported favourable ICERs were school-based programs, nutrition education programs, nutrition assistance programs and community-based physical activity programs. Schwander et al. (2016) reported on public policy interventions as well, but most were limited to school-based programs or the results reported were in terms of DALYs gained, which are outside the inclusion criteria of this review.

2.6 Discussion

Considering the variation in the modelling methods used in the CUAs, such as how individuals transitioned through the models, (either through disease states or by BMI status) and the variance in utility values used in the models, the claims of cost-effectiveness are uncertain. The systematic review of pharmaceuticals by Neovius and Narbro (2008) also critiqued the methods used and how the utility values in the economic models were applied. The utility values (mainly sourced from Hakim et al., (2002) were derived using VAS and not from time trade-off or standard gamble. The study concluded that 'uncertainty still remains about the utility gain associated with weight loss, and the rate of weight regain, and more research is hence called for, as these are highly influential parameters' (Neovius & Narbro, 2008). Similarly, the economic evidence for non-surgical interventions (including pharmaceuticals) in men was judged as highly uncertain (Boyers et al. 2015).

One critical issue with current economic models of obesity interventions is the lack of reporting in the studies on how QoL data was applied, with many not reporting the values used. The systematic review by Ara et al. (2012) noted that QoL data in the models was limited, while another review by Schwander et al. (2016) estimated that only 37% of the studies included in their review provided QoL information. Furthermore, 88% of the studies used QoL values based on published sources, as opposed to collecting QoL data specifically for the study. Given that the chosen utility values in models tend to be one of the main drivers of overall cost-effectiveness results, it is imperative that published models be more transparent.

Economic models constructed using similar Markov models that have used population norms (such as Macran, 2004), or BMI measures derived from cross-sectional data collected through large health surveys (Maheswaran et al., 2013), assume that any transitions to a lower BMI group results in a gain in QoL. This gain in QoL would continue to be incurred for each year the individual remains in that BMI state. These QoL values based on population norms are typically valued using large health surveys collected from a cross-section of the population. Using cross-sectional data does not provide information about changes in weight and the corresponding effect on QoL. Much of the longitudinal evidence has demonstrated that weight loss is not associated with a gain in QoL. Furthermore, given that Markov models are memoryless, movements to lower BMI groups not only attribute higher values of QoL but also ignore any ongoing QoL decrements that may occur from previously being obese. It would be beneficial to quantify the actual change in QoL that is associated with changes in BMI.

Many economic evaluations assume that once an individual loses weight, their QoL is equal to a person with the same BMI, even those who have never been overweight. This is a strong assumption. Rotherberg et al. (2014) argue that cost-utility analyses may underestimate the value of obesity interventions, given that an individual's QoL after weight loss is better predicted by his reduced BMI (Rothberg et al., 2014). The results from this chapter suggest that current cost-utility models are overestimating the gains in QoL from weight loss, given the use of utility values sourced from cross-sectional studies, assumptions or patient populations outside the scope of the study. Further, some studies, such as Rotherberg et al. (2014), are conducted on a small sample and in a clinical setting, so the results may not be generalisable.

The reviews of pharmaceuticals demonstrated that those studies funded by the pharmaceutical manufacturer had more favourable results (all models indicating cost-effectiveness) compared to studies funded externally. The QoL from the trials showed more favourable results for the drug arms. For example, QoL data from four sibutramine trials, analysing the relationship between weight loss and QoL using the SF-36, found a greater gain in utility per kilogram lost for the sibutramine arm compared to the control (placebo) arm. Interestingly, when utility (or QoL) is measured alongside a trial, there are always significant improvements in QoL with a reduction in weight; however, longitudinal studies less frequently demonstrate this relationship. Studies have also demonstrated that those persons seeking surgery for obesity have different QoL than non-seekers, even after controlling for physical characteristic (such as BMI, age and gender) (Kolotkin et al., 2003; Fontaine et al., 2000; van Nunen et al., 2007).

QoL values sourced from trials could produce an over-estimation of effectiveness, as people selected for trials may differ from the general population. This would affect the generalisability of these utility values to other interventions. Generally, people participating in trials are aiming to lose weight and want an intervention to assist them. Furthermore, Dennett et al. (2008) urged caution in using utility weights from different study populations. For example, patients who have Type 2 diabetes may experience greater utility impacts from weight loss than those without this disease.

Another issue with current economic evaluations is the inherent assumption that everyone behaves similarly. Using the 'average person' in models ignores the fact that some people respond to treatment and some do not. The difficulty lies in trying to identify these people and whether current models accurately reflect this. This is an important issue, because it appears that a significant driver in the models was the extent to which regaining weight was taken into account (Neovius & Narbro, 2008; Ara et al., 2012). The actual rate of regain may be underestimated outside a trial setting, which would overstate the cost-effectiveness of these interventions. Overall, there appears to be uncertainty about the inputs into the current models, which calls into question the claims of cost-effective interventions.

2.7 The use of QoL in obesity models

Overall, the studies largely included gains in QoL from weight loss in the models, contradicting current evidence that shows a weak association between weight loss and overall health-related QoL improvement (Warkentin et al. 2014a; Maciejewski et al 2005). Given that the relationship between weight loss and QoL is still poorly understood, current economic evaluations may be overstating the cost-effectiveness of interventions targeting obesity by overestimating QoL gains. The choice of utility measure needs to be appropriate to the population in the model and reflect the link between obesity and QoL, as the choice of utility weight is an important driver of cost-effectiveness. Most studies used utility values based on cross-sectional studies (i.e., based on correlations) and not actual utility values based on changes in weight. In some studies, the utility values were not reported, or the sources were not provided.

Notably, QoL measures suitable for economic evaluation are often omitted from clinical studies. It is important to be able to link the surrogate outcomes commonly reported to QoL, given the increasing evidence that obesity is associated with a decrease in QoL. A typical outcome in clinical trials of interventions aimed at obesity is weight loss; therefore, it is necessary to consider the effect of changing levels of BMI on QoL, not just the average QoL associated with BMI categories. The utility values utilised in these models need to reflect actual QoL changes with weight loss to assess the cost-effectiveness appropriately.

Guidelines recommend a weight loss of at least 5% to reduce the negative health effects of excess weight and comorbidities. However, this level of weight loss may not produce clinically important improvements in QoL (Warkentin et al., 2014c). A recent review of a cohort study of bariatric surgery found that for most of the QoL instruments, a higher weight-loss target would be necessary to achieve improvements in QoL (Warkentin et al., 2014c). This reinforces the suggestion that current economic evaluations of obesity interventions are overstating their cost-effectiveness.

Considering that economic evaluation is an important tool to assess interventions aimed at addressing obesity, understanding the relationship between QoL and obesity is paramount. The QoL measure used in economic evaluations directly estimates the number of QALYs gained as a result of the interventions being evaluated, which is used to construct the ICER, thus providing a relative value for decision-makers to compare against competing demands. For this reason, it is imperative that proper estimates of QoL are used in economic evaluations to determine which interventions are likely to be cost-effective, thus enabling decision makers to determine how to best allocate resources. The next chapter will focus on evaluating the association between QoL and obesity and determining how QoL changes with changes in body weight.

3 QUALITY OF LIFE AND OBESITY

As demonstrated in the previous chapter, economic evaluations tend to use QoL inputs derived from cross-sectional data or trial data in specific populations to quantify the utility gained (lost) from moving from overweight or obese states to normal weight states (and vice versa). Such cross-sectional data are prone to bias, as the results show the association between obesity and QoL whereas what is essential in economic modelling is to understand whether a change in BMI is causally related to a change in QoL. Many studies use only cross-sectional data to evaluate the relationship between QoL and obesity (Tsai et al., 2005), demonstrating that obesity is associated with impaired health-related QoL (Jia & Lubetkin, 2005). The use of panel data may provide a better appraisal of the movements between BMI states to derive the corresponding QoL changes, as any unobserved heterogeneity can be accounted for and changes over time can be assessed.

The cross-sectional nature of the link between obesity and QoL has been well studied, with a clearly established relationship between obesity and lower health-related QoL (Cameron et al., 2012). There exists however, only weak evidence for the longitudinal association between weight change and QoL (Fontaine & Barofsky, 2001, Laxy et al., 2014). A report by the AIHW has stated that ‘longitudinal research into factors associated with overweight and obesity, such as changing patterns of health, nutritional status, vulnerable populations and education could provide further public health benefits for Australians’ (AIHW, 2016a). Monitoring trends of overweight and obese individuals over time, and within specific groups, is required to better inform policy development. Furthermore, the evidence is lacking for the effect of BMI on preference-based health outcome measures, such as QALYs, which is important for the assessment of interventions aimed at overweight and obese individuals (Kortt & Dollery, 2011).

3.1 Review of the literature

A literature review was conducted to identify relevant literature that has explored the link between QoL and BMI. The details of the search strategy can be found in Appendix 5. The goal of weight-loss interventions is to reduce not only participants’ weight, but also the comorbidities and increased mortality associated with excess weight. Weight-loss interventions have been shown to reduce blood pressure, blood lipid levels and cholesterol, which may lead to longer-term health benefits – for example, reduced risk of diabetes (Franz et al., 2007). Other expected outcomes of reduced weight are increases in QoL in terms of general well-being, as well as in physical and mental health. However, the question remains of whether there are significant gains in QoL following weight loss. A systematic review of RCTs did not find meaningful changes in QoL following weight-loss interventions (Maciejewski et al., 2005). Similar results from a meta-analysis found no significant associations between weight loss and improvements in health-related QoL (Warkentin et al., 2014a). The most recent systematic review of US trial data of reported QoL and weight loss concluded that improvements in health-related QoL were more significant for physical and not mental QoL after weight loss (Kroes et al., 2016) Another review of RCTs suggests while there is evidence of clinical effects of weight-loss interventions, the evidence in terms of QoL is lacking (Maciejewski et al., 2005).

3.1.1 Cross-sectional studies

The majority of the literature evaluating obesity and QoL has been based on cross-sectional data. A number of studies have found that being overweight or obese is associated with impaired health-related QoL (de Zwaan et al., 2009; Dey et al., 2013; Doll et al., 2000; Ford et al., 2001; Han et al., 1998; Hassan et al., 2003; Hopman et al., 2007; Huang et al., 2006; Jia & Lubetkin, 2010; Kearns et al., 2013; Kortt & Dollery, 2011; Larsson et al., 2002; Renzaho et al., 2010; Serrano-Aguilar et al., 2009; Soltoft et al., 2009; Sturm & Wells, 2001; Yancy et al., 2002). A review by Dennett et al. (2008) observed that, regardless of the utility measure used or the study population examined, an increase in body mass was associated with reductions in QoL. Han et al. (1998) noted that less is known about weight and QoL in the general population. Macran (2004) explored this relationship with general population data using the 1996 Health Survey for England and found that most of the apparent relationship between BMI and health-related QoL could be attributed to age and the presence of a long-standing illness.

The evidence suggests that the impact of obesity is more pronounced on physical health rather than mental health (Sach et al., 2007; Yan et al., 2004b; Brown et al., 2000; Franco et al., 2012; Hassan et al., 2003; Yancy et al., 2002; Ford et al., 2001; Jia & Lubetkin, 2005; Katz et al., 2000; Larsson et al., 2002; Han et al., 1998; Huang et al., 2006; Cameron et al., 2012; Vasiljevic et al., 2008). Furthermore, it appears that physical health is only reduced in obese and not overweight individuals (Ford et al., 2001; Jia & Lubetkin, 2005; Hassan et al., 2003; Yancy et al., 2002).

Conversely, some studies demonstrate no difference or an increase in QoL for overweight compared to normal weight individuals (Ul-Haq et al., 2013; Vasiljevic et al., 2008; Bentley et al., 2011). Ul-Haq et al. (2013) suggests that this is driven by higher mental QoL scores for overweight individuals. A few studies have also noted reduced QoL in the mental health dimensions with greater BMI (Doll et al., 2000; Ford et al., 2001; Finkelstein, 2000; Hassan et al., 2003; Kim et al., 2007; Brown et al., 1998); however, the association is weaker than with physical QoL (Yan et al., 2004a; Heo et al., 2003; Katz et al., 2000). Interestingly, individuals who engage in physical activity have higher QoL at all BMI scores (Jia & Lubetkin, 2005). Some studies have demonstrated that the existence of chronic conditions has more impact on QoL and explains the reduction in QoL (Warkentin et al., 2014b). However, other studies have found lower QoL associated with increased levels of obesity in the absence of these conditions (Jia & Lubetkin, 2005). Cross-sectional studies in obese children and adolescents have also found that most dimensions of QoL are impaired and this impairment worsens as the severity of obesity increases (Buttitta et al., 2014).

3.1.2 Longitudinal studies

Reviews of trials of surgical and lifestyle interventions have demonstrated that intentional weight loss in obese individuals is associated with improvements in QoL. However, these trials usually have short follow-up periods of 1–2 years, although some extend to five years (Fontaine & Barofsky, 2001; Kolotkin et al., 2001; Picot et al., 2009). Less is known about any association between changes in weight and QoL in a general population and over longer periods of time (Milder et al., 2014; Burns et al., 2001; Verkleij et al., 2013). The longitudinal literature has demonstrated that increased BMI is associated with reductions in physical health-related QoL, which was more pronounced in women than men (Muller-Nordhorn et al., 2014; Cameron et al., 2012; Stafford et al., 1998). Contrary to the results of cross-sectional studies, one longitudinal study reported that weight gain led to improvements in mental QoL (most significant in women) and another reported this result only in women (Laxy et al., 2014; Verkleij et al., 2013). This differed from the results reported by Fine et al. (1999), who observed an association between weight gain in overweight and obese women and a reduction in mental health QoL scores. Burns et al. (2001) found a reduction in QoL with weight gain greater than 10% of initial body weight, but only in older women. The majority of the studies showed no association or a weak association between changes in weight and mental health (Hopman et al., 2007; de Zwaan et al., 2009; Doll et al., 2000; Fontaine & Barofsky, 2001).

When exploring weight changes, weight gain was associated with a lower QoL (Döring et al., 2015; Verkleij et al., 2013; Laxy et al., 2014). However, weight loss had no significant preventative effect (Döring et al., 2015; Laxy et al., 2014; Milder et al., 2014). Döring et al. (2015) also found no association between BMI categories and anxiety/depression; a similar finding was made in previous studies which showed a weak or no association with anxiety/depression (de Zwaan et al., 2009; Dey et al., 2013; Doll et al., 2000; Hassan et al., 2003; Jia & Lubetkin, 2010; Larsson et al., 2002; Macran, 2004). An older study investigating weight fluctuations found that steady weight gain or weight fluctuations had no effect on physical functioning in men (Stafford et al., 1998). Results from The Diabetes Prevention Program, a large multi-centre RCT (N=3,206), showed that weight was independently associated with a change in SF-6D score, with an increase of 0.007 in utility for every five kilograms lost (Ackermann et al., 2009).

Model specifications

Many of the longitudinal studies examining the association between QoL and obesity (or weight change) used weight-change groupings (such as ‘weight gain’, ‘stable weight’, ‘weight loss’), with some further splitting weight gain/loss into ‘moderate’ and ‘heavy’ (Milder et al., 2014; Laxy et al., 2014; Döring et al., 2015). Other studies evaluated the change in QoL on BMI categories or used BMI as a continuous variable in the models. The dependent variable used in most studies, was QoL derived from the SF-36 or SF-12 (except for Daviglus et al., 2003; Döring et al., 2015; and Zaninotto et al., 2010, who used the HSQ-12, EQ-5D and CASP19 respectively). In the statistical analyses reported, QoL was mostly used as a continuous variable and the summary scores for physical and mental health. Only one study (Kortt & Dollery, 2011) used the SF-6D utility score as the outcome variable of interest. There was variation in the statistical techniques used to analyse the data. Non-parametric techniques (such as Kruskal-Wallis or χ^2 tests) were used to evaluate weight change. Many employed ANOVA or linear regression and another popular option was the generalised estimating equation (GEE). The benefits of employing a GEE model is that it considers the continuous nature of the dependent variable. All studies adjusted the models for demographic and economic variables and survey year.

3.1.3 Australia-specific studies

Renzaho et al. (2010) assessed the associations between the eight domains of the SF-36 and obesity, using wave 7 from the HILDA survey (Renzaho et al., 2010). The analysis controlled for age, gender, geographic location, smoking status, Aboriginal status, severe disability and education attainment, but did not examine the SF-6D utility weights specifically. The results showed that both low and high BMIs were associated with decreasing levels of both physical and emotional well-being; however, the impact was stronger on physical health aspects.

Kortt and Clark (2005) used the Australian 1995 National Health Survey (NHS) to assess the relationship between BMI and utility for both males and females; in this study the utility scores were converted into quality-adjusted life expectancy and the results showed a negative association between increased BMI and utility (Kortt & Clarke, 2005). A more recent analysis by Kortt and Dollery (2011) using the HILDA survey found that higher BMI is negatively associated with utility, based on cross-section results. The panel nature of HILDA was also used and the authors found that only the presence of arthritis and depression/anxiety were statistically significant in predicting a change in utility in the sample (Kortt & Dollery, 2011).

3.1.4 Meta-analysis of BMI and QoL

A meta-analysis that reviewed the association between BMI and QoL using the SF-36 found that adults with higher-than-normal BMI had significantly reduced QoL, as measured using the physical component of the SF-36 (Ul-Haq et al., 2013). However, the patterns were different for the mental health component of the SF-36; compared to individuals with normal weight, those with BMIs greater than 40 had significantly lower mental health scores, while overweight individuals had significantly higher mental health scores. A more recent meta-analysis of RCTs of weight-loss interventions (N=53) found no significant associations between weight loss and improvements in QoL using a contingency table approach[15] (Warkentin at al 2014a). A meta-analysis included in the review used a subset of the studies to assess the domains of the SF-36. The finding suggested that weight loss resulted in improvements in physical health, but not mental health. Table 3.1 summarises the longitudinal studies exploring the relationship between BMI or weight changes on health-related QOL.

[15] A contingency table approach is a non-parametric analysis that uses information for all included studies to test for significant differences (but weights all the studies equally). Warkentin et al. 2014a compared statistically significant weight loss (yes/no) with statistically significant health-related QoL improvement (yes/no) for all studies and used Fisher's exact tests to determine any significant associations.

Table 3.1 Longitudinal studies of obesity and QoL

Author	Country	Study Type	Time period	N	QoL Instrument	Analysis	Results
Stafford 1998	UK	Survey of civil servants (53–55 years)	6–8 years	10,308	SF-36	OLS	Obesity and weight changes associated with poor physical functioning
Fine 1999	US	Nurses Health Study Cohort	4 years	75,453 women	SF-36	OLS	Weight gain associated with decreased physica function, vitality and , and increased bodily pain.
Burns 2001	Netherlands	Survey from Risk Factors for Chronic Diseases project	5 years	1,113	SF-36	ANOVA	Measured and perceived obesity were associated with reduced physical functioning
Leon-Munoz 2005	Spain	Survey general population	2 years	2,364	SF-36	OLS	Weight change associated with worse HRQL among older adults (mostly women)
Daviglus 2008	US	Cohort study (middle aged)	26 years	6,766	HSQ-12	General linear models	Higher BMI in middle age associated with worse QoL in older ages
Zaninotto 2010	UK	English Longitudinal Study of Ageing (ELSA)	2 years	7,114	CASP19	OLS, logit	For a given BMI, higher WC related to poor QoL and depressive symptoms in women
Verkleij 2012	Netherlands	Cohort study	5 years	2,414	SF-36	GEE	Weight change leads to a reduction in physical health and improvement in mental health for women
Cameron 2012	Australia	Australian Diabetes, Obesity and Lifestyle Study	5 years	5,985	SF-36	OLS, logit	Obesity associated with deterioration in health-related QoL, both physical and mental
Milder 2013	Netherlands	Population based cohort study	5 years	4,135	SF-36	GEE	Weight gain and weight loss associated with unfavourable change in QoL (weight gain with physical and weight loss with mental)
Laxy 2014	Germany	Survey of general population	7 years	3,080	SF-12	ANOVA χ^2	Weight gain leads to impairment in physical health
Seppala 2014	Finland	Survey of general population	3 years	2,752	SF-36	Kruskal-Wallis or χ^2	Weight gain associated with worse results in physical and mental QoL
Muller-Nordhorn 2014	Germany	ORBITAL study (high risk cardiovascular diseases)	3 years	6,726	SF-12	Linear mixed regression	Increases in BMI associated with decreases in physical QoL. Mental health increases with BMI
Döring 2015	Sweden	Public health survey general population	8 years	31,182	EQ-5D	GEE	Weight gain leads to impairment in QoL irrespective of baseline BMI

Note- HILDA: Household, Income and Labour Dynamics in Australia, CASP19: Control, autonomy, self-realisation and pleasure, SF-36: Short-form health survey, EQ-5D: EuroQol group (5 dimensions), HSQ-12: Health status questionnaire, OLS: Ordinary least squares, GEE: generalised estimating equations, ANOVA: analysis of variance

3.1.5 Summary of the literature

Overall, although weight gain has a greater effect on QoL than weight loss (Laxy et al., 2014), it does not appear that weight loss reverses this effect (Burns et al., 2001). The literature also suggests that the burden of obesity may impact physical health more than mental health. Studies that have estimated utility values associated with obesity indicate that there is a negative relationship between BMI and utility, but there is wide variability in the estimates (Dixon et al., 2004). Much of the literature on QoL has focused on studies using a cross-sectional design or from RCT data in specific populations. There exists only weak evidence for the longitudinal association between weight change and QoL (Fontaine & Barofsky, 2001; Laxy et al., 2014). The implications of these results have a significant bearing on the assumptions about QoL gains associated with weight loss in cost-utility economic evaluations. Interventions reporting QoL gains and, more critically, extrapolating these QoL gains into the future, have the potential to overestimate the QoL gains and thus the cost-effectiveness of interventions. Although there is weak evidence, cost-effectiveness studies continue to use models that directly evaluate weight loss and the resulting impact on QALYs. Again, there are questions as to whether this is appropriate, especially for models being applied to a general population.

This chapter aims to add to the literature by using a large longitudinal panel dataset, the Household Income and Labour Dynamics in Australia Survey (HILDA), to evaluate the effect of changes in BMI on an individual's overall health-related QoL. Currently, there are 16 waves of HILDA data (10 waves with BMI) that can provide a longer time to study weight fluctuations, as changes to weight and the resulting comorbidities tend to occur over longer lengths of time.

The HILDA dataset is representative of the general population, which encompasses changes across all BMI categories – unlike RCT longitudinal data, which mostly relates to obese individuals over a shorter period of time. The advantage of using a panel dataset is the ability to control for unobserved differences in individuals (such as ability or cultural factors) and study dynamic changes in the long run. The models can be estimated to incorporate the differences between respondents (R1 vs R2), as well as the differences across individuals over time ($R2_{t=1}$ vs $R2_{t=2}$) (Figure 3.1).

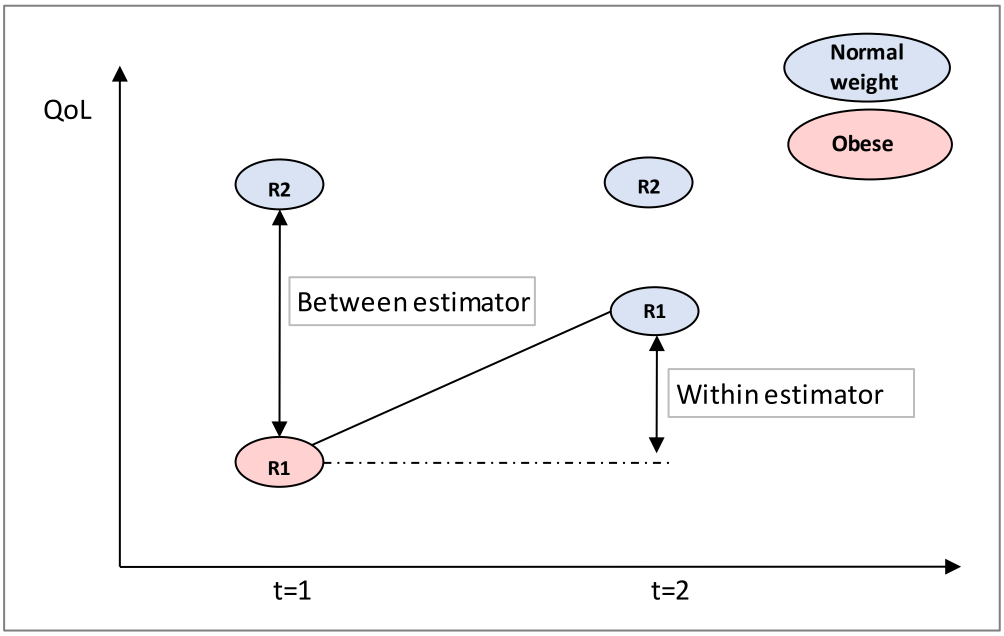


Figure 3.1 Panel data analysis

An important addition to the literature is that the analysis will take advantage of the SF-36 summary utility score (SF-6D) to assess effects on QoL in terms of utility scores. This chapter will explore whether it is appropriate to apply utility values stratified by BMI group and apply higher QoL solely based on weight loss, and whether the use of utility values sourced from cross-sectional studies leads to an overestimation of the QoL gain in these models, and will estimate the effect of weight changes on QoL (Birkenbach, 2017).

3.2 Methods

3.2.1 Data

The HILDA[16] survey is a nationally representative household-based longitudinal survey (of 19,914 individuals from 7,682 households in wave 1), collected annually since 2001. In wave 11, an additional 2,153 households and 5,477 individuals were added to the panel in a top-up sample. The design of the survey is based on that of other household-based surveys, notably the German Socio-Economic Panel (GSOEP) and the British Household Panel Survey (BHPS) (Wooden & Watson, 2007). The HILDA project is funded through the Australian Government Department of Social Services. Funding for the survey was granted for 16 waves, although the survey is designed to continue for longer than this. The survey collects information about economic and subjective well-being, labour market dynamics and family dynamics. Most

[16] All documentation for the HILDA survey can be found at https://melbourneinstitute.unimelb.edu.au/hilda

questions are repeated each year; however, major modules (for example, wealth and health) are only conducted in particular waves.

Sample selection

The sampling unit of the survey is the household, rather than the individual, with the household is defined as 'a group of people who usually reside and eat together'.[17] The households were selected using a multi-staged approach in which 488 areas were selected from across Australia based on the 1996 Census Collection Districts (CDs), stratified by state.[18] Within each of the CDs, 22 to 34 dwellings were selected (dependent on the response and occupancy rates of the area) and, within each dwelling, up to three households were chosen to be a part of the HILDA sample (Watson & Wooden, 2002).

Survey population

The reference population of the HILDA survey was intended to represent all usual residents of private dwellings in Australia (excluding persons living in remote parts of Australia). Persons residing in non-private dwellings such as hospitals, motels and prisons were excluded from the wave 1 sample; however, future waves will capture those respondents in wave 1 who move into institutions. All members of the survey in wave 1 are intended to be followed over an indefinite lifetime and form the basis of the life panel. The sample is extended over time by additions to the household based on the following conditions:

- any children born to or adopted by members of the households
- new household members resulting from changes in the composition of the household
- a new household member who arrived in Australia for the first time after 2001.

Appendix 6 outlines certain sample characteristics of the HILDA population, compared to the ABS monthly Population Survey from wave 1. Continuing sample members (CSMs) include all members from wave 1 including any children, new entrants to a household who have a child with a CSM, and new immigrants to Australia. All CSMs remain in the sample indefinitely. All other people who share a household in wave 2 or later are considered Temporary Sample Members (TSMs) (Summerfield et al., 2017).

[17] The HILDA survey used this definition as it is similar to the definition used by the ABS.
[18] The five largest states were further stratified in terms of population and by metropolitan and non-metropolitan regions.

In wave 11, a top-up sample of 2,153 households was added to the survey. Given the HILDA sample cannot mimic the population in terms of immigration as it progresses over time, the top-up sample was added to reduce this bias associated with immigration. The top-up sample was designed to capture immigrants permanently settling in Australia since 2001, long-term visitors arriving since 2001, Australians not in Australia in 2001 who have since returned from overseas, and Australian-born children of the first three groups (Watson, 2011).

Survey instrument

In wave 1, the survey comprised four different instruments:

- the Household Form (HF) records basic information about the composition of the household
- the Household Questionnaire (HQ) collects information about the household rather than the individual, mainly covering child care arrangements, housing, household spending and household wealth
- the Person Questionnaire (PQ) is administered to every member of the household 15 years and over
- the Self-Completion Questionnaire (SCQ), which all persons completing a PQ are asked to fill out to return at a later date; it comprises mostly attitudinal questions to which respondents may feel uncomfortable responding in face-to-face interviews.

In the subsequent waves the PQ questionnaire was replaced with two instruments:

- the Continuing Person Questionnaire (CPQ)
- the New Person Questionnaire (NPQ).

The files provided by the HILDA survey include the household file (all information from the HF and HQ); enumerated person file (all responding households and contains limited information from the HF); responding person file (all persons who provided an interview, including CPQ/NPQ and SCQ); and the combined file (a combination of the three files above). For the analyses, the combined file was used to construct a dataset. All waves were used to construct a dataset that included each available wave of data for each respondent that spanned 2001–2015. A wave variable was constructed to denote each wave in the dataset.

3.2.2 Quality of life variables

One of the measures the HILDA survey uses to capture health-related QoL is the Short Form-36 (SF-36). The SF-36 is a 36-item health survey that provides a summary measure of health-related QoL across eight health dimensions: physical functioning, role-physical, bodily pain, general health, vitality, social functioning, role-emotional and mental health (Ware & Sherbourne, 1992). The SF-36 is the most widely used generic measure of health status and enables researchers to compare QoL over time and across age groups and medical conditions, as well as between individuals (Fontaine & Barofsky, 2001). The scores for each of the dimensions are evaluated on a scale from 0 to 100. The higher the score, the better health or well-being individuals experience for that domain.

The eight-scale profile of the SF-36 can also be reduced into two psychometrically-based summary measures of physical and mental health (Ware et al., 2007). Physical functioning, role-physical and bodily pain contribute to the Physical Component Summary (PCS) measure, whereas mental health, role-emotional and social functioning contribute to the Mental Component Summary (MCS) measure (Figure 3.2). The calculation of the MCS and PCS summary scores is conducted in a three-step process. Each of the specific domains is standardised using a Z-score transformation of means and standard deviations from the 1995 National Health Survey (NHS)[19]. These Z-scores are then aggregated using the coefficients from the 1995 NHS as weights. Finally, the scores are transformed to have a mean of 50 and a standard deviation of 10. The scoring algorithm[20] can be found in Appendix 7.

The method of transforming the data into the summary scores has been criticised as it results in negative coefficients for some of the domains (Taft et al., 2001). The orthogonality of the summary scores assumes the two aspects of health and well-being are uncorrelated (Laucis et al., 2015), which may not reflect the true nature of some health conditions. The original instructions suggest using the summary scores in combination with the domain scores before making any conclusions (Ware & Kosinski, 2001).

[19] 1995 National Health Survey – SF-36 Population norms: http://www.ausstats.abs.gov.au/ausstats/free.nsf/0/AF34940625286915CA257225000495F3/$File/43990_1995.pdf

[20] Source: Australian Longitudinal Study on Women's Health http://www.alswh.org.au/images/content/pdf/InfoData/Data_Dictionary_Supplement/DDSSection2SF36.pdf

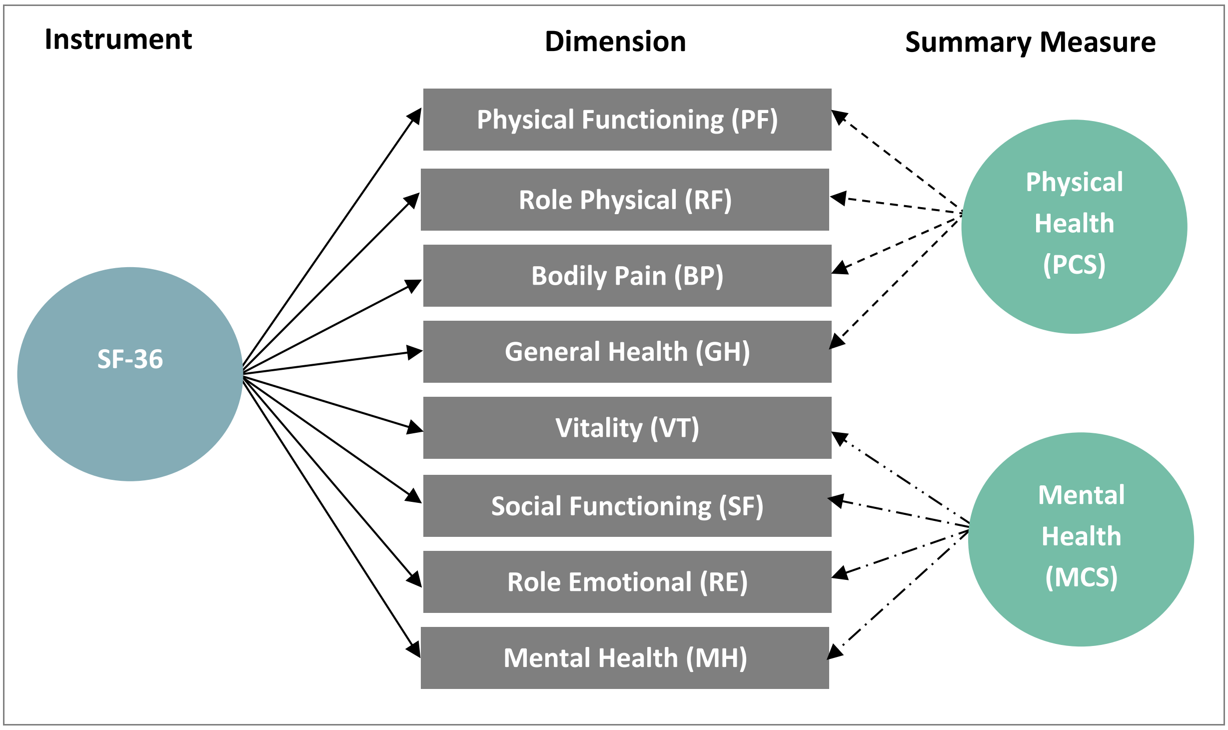


Figure 3.2 Model of the SF-36 Health State Questionnaire

The SF-36 has been included in the HILDA survey since the first wave due to its widespread use internationally, as well as its inclusion in the 1995 National Health Survey conducted by the Australian Bureau of Statistics (ABS) (Wooden, 2009). Self-reported measures of health are increasingly being used in survey research to incorporate the patient's point of view and the complex multi-faceted nature of health.

As stated in the HILDA user manual, 'the SF-36 Health Survey is an internationally recognised diagnostic tool for assessing functional health status and well-being'. It is a widely used instrument and has been documented in over 1,000 publications (Ware, 2000). An Australian study assessing the validity of the SF-36 in the HILDA survey (using wave 1) for assessing health inequalities concluded that the eight scales of the SF-36 were 'psychometrically sound, with good internal consistency, discriminant validity and high reliability', supporting its use as a general outcome measure of health status (Butterworth & Crosier, 2004). The study further found that SF-36 scales demonstrated patterns in terms of physical and mental health, demographic characteristics and health inequalities consistent with previous research.

The SF-6D utility weights

The SF-36 was not specifically designed for use in economic evaluation, as it does not explicitly incorporate preferences into the scoring algorithm (Brazier et al., 2002).21 However, given the SF-36 is widely used in clinical trials, generating health state utility values which are needed to estimate QALYs from a preference-based measure extends the scope of its usage (Brazier et al., 2007). A team at the University of Sheffield developed the SF-6D, a preference-based utility score to measure health status, to allow for the extension of the SF-36 to economic evaluation. The HILDA survey includes this transformed SF-6D utility weight in the dataset, derived by applying the scoring algorithm to the raw SF-36 QoL data. The SF-6D has six dimensions (physical functioning, role limitation, social functioning, pain, mental health and vitality) and defines 18,000 health states using the SF-36 (Kharroubi et al., 2005). Adopting a standard gamble approach22 from a sample of the United Kingdom general population, a total of 249 states were defined by the SF-6D. The SF-6D measures an individual's QoL from 0 (state indicating death) to 1 (best measured health state). It is possible to obtain utility values less than 0, denoting health states considered worse than death.

3.2.3 BMI and weight variables

Data about height and weight have been collected in the HILDA survey since wave 6, providing 10 waves of BMI data available for analysis. The BMI variable in the survey is not measured[23] but is based on each respondent's answers to the questions: '*what is your current weight?*' and '*how tall are you (without shoes)?*' These questions are not collected as part of the personal interview but asked in the self-completion questionnaire.[24] The HILDA survey coded any respondents with implausible values with a missing value code, after using a two-stage process to inspect high and low values of height and weight (Wooden et al., 2008). The HILDA survey was compared to the 2004–05 National Health Survey (NHS) collected by the ABS, with the results showing that there was a greater proportion of obese people in the HILDA survey in

[21] The SF-6D algorithms to apply to SF-36 or SF-12 data are available for non-commercial use (http://www.shef.ac.uk/scharr/sections/heds/mvh/sf-6d)

[22] The standard gamble is a technique for valuing health states that gives the respondent a choice between 1) a certain intermediate outcome and 2) the uncertainty of a gamble of two possible outcomes, where one of the two possible outcomes is considered better than the certain intermediate outcome and one is considered worse. (Brazier et al. 2007)

[23] As previously discussed in section 1.2, self-reported height and weight estimates are likely to suffer from bias; nevertheless, in the absence of measuring actual body fat percentage, BMI calculated using these responses is considered one of the best indicators of healthy body weight

[24] The self-completion questionnaire (SCQ) is usually completed without assistance from the HILDA survey interviewers. It states in Wooden et al (2008) that the decision to include height and weight in the SCQ was conducted due to concerns of a longer interview time as well as concerns that respondents might be embarrassed or even offended by being asked questions about their weight.

wave 6. A comparison of all waves used in our analysis of the ABS NHS data is included in the summary statistics for reference (see section 3.4).

An initial exploration of the data demonstrated the non-linearity of BMI with regards to QoL, with significant coefficients on quadratic and cubic functions. Therefore, BMI was specified in five categories for the analyses. Extreme values (such as a BMIs of 8 or 93.5) were examined to assess the height and weight for any errors in calculations. Values were matched to previous waves and all reporting errors corrected. For extreme values where no error could be found, the data point was transformed into a missing variable. Based on the BMI reported in the HILDA data, dummy variable BMI groups were constructed to denote underweight, normal weight, overweight, obese and severely obese, based on the WHO classification (see Table 1.1). Specifying the data into BMI categories provides additional information in terms of the effect of QoL for each weight group versus a unit change in BMI. Subjects with no data on BMI were coded as a separate dummy variable to explore any bias in non-responders. Pregnant women were also excluded from the analysis.

BMI change groups

To analyse changes in BMI status over time, lagged variables were constructed to compare an individual's BMI status in previous waves. A variable was constructed to denote an individual's BMI status in the previous wave to compare one-year BMI group movements. A one-year movement was assumed appropriate as most economic models assume a one-year cycle length. A cross-tabulation of the current wave BMI category and the previous wave BMI category was undertaken to determine the movements of individuals between the different categories. Table 3.2 outlines the number of individuals moving to each BMI category over a one-year period.

Table 3.2 One-year movements between BMI categories (HILDA waves 6-15)

		Previous Wave				
		Underweight	**Normal weight**	**Overweight**	**Obese**	**Severely obese**
Current Wave	**Underweight**	1,403	861	47	4	4
	Normal weight	1,105	32,358	4,544	213	47
	Overweight	39	5,577	25,446	2,856	159
	Obese	5	252	3,449	10,227	1,237
	Severely obese	3	36	171	1,651	5,481

BMI group change variables were then generated. Multiple BMI groups were combined to allow for a larger sample size and realistic movements over a one-year time frame, resulting in 16 BMI change groups. For example, movements from underweight to normal, overweight, obese or severely obese in year 1 were all grouped together, as very few people move from underweight to obese in one year. Each variable was then coded a 1 or 0 to denote 'movement occurred between these BMI groups' or 'no movement occurred between these BMI groups'. Individuals were only classified in one of the BMI movement groups at any one time. In the case of the variables where an individual remained in the same BMI group, a 1 denoted 'stayed in current BMI group' and a 0 denoted a movement elsewhere. Each variable was used in the regression analysis as a dummy variable and the resulting QoL change estimated compared to that associated with remaining in the normal weight category. Figure 3.3 displays the weight change groups for waves 6–15, constructed from nine yearly BMI change data points across then ten waves and sixteen possible weight change categories per survey respondent.

<table>
<tr><th colspan="2"></th><th colspan="5">Previous wave</th></tr>
<tr><th colspan="2"></th><th>Underweight</th><th>Normal Weight</th><th>Overweight</th><th>Obese</th><th>Severely Obese</th></tr>
<tr><th rowspan="5">Current wave</th><th>Underweight</th><td>1</td><td>7</td><td rowspan="2">10</td><td rowspan="2">12</td><td rowspan="3">15</td></tr>
<tr><th>Normal Weight</th><td rowspan="4">6</td><td>2</td></tr>
<tr><th>Overweight</th><td>8</td><td>3</td><td>13</td></tr>
<tr><th>Obese</th><td rowspan="2">9</td><td rowspan="2">11</td><td>4</td><td>16</td></tr>
<tr><th>Severely Obese</th><td>14</td><td>5</td></tr>
</table>

Underweight no change (1)	*No change*
Normal weight no change (2)	*No change*
Overweight no change (3)	*No change*
Obese no change (4)	*No change*
Severely obese no change (5)	*No change*
Underweight to normal weight/overweight/obese/severely obese (6)	*Weight gain*
Normal weight to underweight (7)	*Weight loss*
Normal weight to overweight (8)	*Weight gain*
Normal weight to obese/severely obese (9)	*Weight gain*
Overweight to normal weight/underweight (10)	*Weight loss*
Overweight to obese/severely obese (11)	*Weight gain*
Obese to normal weight/underweight (12)	*Weight loss*
Obese to overweight (13)	*Weight loss*
Obese to severely obese (14)	*Weight gain*
Severely obese to underweight, normal weight, overweight (15)	*Weight loss*
Severely obese to obese (16)	*Weight loss*

Note: The red squares represent weight gain, the green squares weight loss and the grey squares steady weight.

Figure 3.3 Weight change groups by wave

Weight gain/loss

To analyse fluctuations in weight, five[25] distinct groups were created as dummy variables to represent annual weight changes. A change in body weight percentage was created using each wave's current weight variable and the lagged weight variable. The five groups were created as follows:

- Heavy weight gain: ≥ 10% of body weight gained
- Heavy weight loss: ≥ 10% of body weight lost
- Weight gain: ≥ 5% and < 10% of body weight gained
- Weight loss: ≥ 5% and < 10% of body weight lost
- Steady weight: < 5% of body weight lost and < 5% of body weight gained

These variables were used to explore the effect of weight change on QoL over the 10 waves of data.

3.2.4 Socioeconomic and demographic variables

Selected socioeconomic and demographic variables were used in the final models to control for other factors that could be simultaneously impacting on QoL. Other health variables were also included that could be impacting on QoL to a greater extent than high body mass.

Education

In the HILDA dataset, the education variable captured '*the highest level of education obtained*'. The levels captured were (1) postgrad – masters or doctorate, (2) grad diploma, grad certificate, (3) bachelor or honours, (4) advanced diploma, diploma, (5) certificate III or IV, (6) certificate I or II, (7) certificate, not defined, (8) year 12, and (9) year 11 and below. The education questions used to derive the variables in HILDA were based on the Australian Standard Classification of Education (ASCED) (Summerfield et al., 2017). In this analysis, the education categories were grouped into the following three categories: (1) year 11 or below, (2) year 12, certificate or diploma, and (3) degree or higher. These categories were included as dummy variables in the analysis.

Gender

The gender of each household member is also collected for each wave in HILDA. Dummy variables were generated to denote the gender of the respondents.

[25] Initially only three groups were derived (weight gainers, weight losers or stable weight); however, after running analysis with highly statistically significant results for the weight gainers, it was decided to break these groups further down into heavy weight gain and heavy weight loss.

Income

The HILDA survey collects detailed information about income, including market income (wages and salary, business income, investment income, private pensions), private transfers, Australian public transfers (both government income support and non-income support payments), foreign pensions and other public transfers. The HILDA dataset derives variables to represent gross income, disposable income and estimated taxes using all the above income sources. In this analysis, a variable was constructed to denote household gross income, by combining the positive and negative income variables captured in HILDA dataset.

Given the existence of economies of scale in consumption within households (where the needs of a household grow with each additional member, but not in a proportional way), an equivalence scale was used to take into account the size of the household, including adults and children. The rationale for this is that household consumption will not be three times as high for a household with three members as it is for a single person. The OECD-modified scale was used; this assigns a value of 1 to the household head, 0.5 to each additional adult member and 0.3 to each child. Therefore, a three-member household with 2 adults and a child would only require an income 1.8 times [1+0.5+0.3] that of a single person household to have equivalent income.[26] A weighted gross income variable was constructed using the following equation:

$$equivalent\ income\ = \frac{total\ gross\ income}{1 + 0.5 * (adults - 1) + 0.3 * (children)}$$

The log (base e) transformation of income was included in the analysis to transform the income data into a linear relationship, given the skewness of the income variable. Quintiles of OECD equivalised income were also generated for each wave. Income quintiles, which divide the population into five equal groups, are useful for making comparisons across waves, as well as across survey respondents, using income as an indicator of socio-economic status.

Age

In the HILDA data, the age variable is the age at last birthday as of 30 June immediately preceding the fieldwork for that wave. The age variable is provided in the HILDA dataset as a continuous variable. To better estimate the effect of age on QoL over the life span, age

[26] There are two other equivalence scales used by the OECD. The 'OECD equivalence scale' assigns a value of 1 to the first household member, 0.7 to each additional adult and 0.5 to each child. This scale is considered to be the 'old' OECD scale. There is also the square root scale which divides household income by the square root of the household size. The OECD modified scale results in equivalence estimates between the other two scales. http://www.oecd.org/social/publicationsdocuments/statisticalsourcesandmethods/

categories were constructed. Given that the relationship between age and QoL is not linear, ten-year age categories starting from age 15 and ending at 74, plus a final age category of 75 and over, were included in the model.

Marital Status

Current marital status is captured in the HILDA survey by asking the respondents '*Which of these best describes your current marital status?*': (1) Married (in a registered marriage), (2) Separated but not divorced, (3) Divorced, (4) Widowed, (5) Never married but living with someone in a relationship, or (6) Never married and not living with someone in a relationship. Three dummy variables were used to represent marital status were constructed: (1) married or living together, (2) separated, divorced or widowed, and (3) single.

Remoteness

HILDA includes a remoteness area variable derived from the Accessibility/Remoteness Index of Australia (ARIA) scores from the 2001 Census. The remoteness score is a derived variable from the statistical local area[27] and combines respondents into five groups: (1) Major city, (2) Inner Regional Australia, (3) Remote Australia, (4) Very Remote Australia and (5) Migratory. Using these data, a variable was constructed to denote a metropolitan area that included major cities and inner regional Australia. A second variable was constructed to denote a non-metropolitan area that included the other three region categories.

Employment Status

The HILDA dataset also includes a derived variable on 'current employment status' that groups respondents into four categories: (1) employee, (2) employer, (3) own-account worker, and (4) contributing family member. Another derived variable was used to describe broad labour force. This variable grouped respondents as (1) employed, (2) unemployed or (3) not in the labour force. Another variable asked respondents '*Which of these categories best describes your main activity since you last worked or looked for work?*': (1) Retired/Voluntarily Inactive, (2) Home duties/Child care, (3) Study, school, TAFE or university, (4) own illness, injury or disability, (5) Looking after ill or disabled person, (6) Travel, on holiday, leisure activities, (7) working in an unpaid voluntary job, or (8) other activity. These questions were combined to construct employment status variables. Subjects were coded as employed, self-employed, unemployed, unpaid housework, retired, student or other; all variables were included as dummy variables.

[27] The statistical local area (SLA) codes are based on the 2001 Census Collection District. The general release of HILDA does not include geographical descriptors for SLA.

Long-term health conditions

In each wave of the HILDA survey respondents are asked: *'Do you have any long-term health condition, impairment or disability (such as these) that restricts you in your everyday activities, and has lasted or is likely to last, for 6 months or more?'*. The list of long-term health conditions that the respondents were presented included:

- sight problems not corrected by glasses or contact lenses
- hearing problems
- speech problems
- blackouts, fits or loss of consciousness
- difficulty learning or understanding things
- limited use of arms or fingers
- difficulty gripping things
- limited use of feet or legs
- nervous or emotional conditions that require treatment
- any restriction that limits physical activity or physical work (e.g., back problems, migraines)
- any disfiguration or deformity
- any mental illness that requires help or supervision
- long-term effects as a result of a head injury, stroke or other brain damage
- a long-term health condition or ailment that is still restrictive even though it is being treated or medication is being taken for it
- any other long-term health condition such as arthritis, asthma, heart disease, dementia or any other long-term condition.

A further question asked respondents, '*Does your condition/do your conditions limit the type of work or the amount of work you can do?*'. The response options for the respondent were: long-term health conditions limit type or amount of work; long-term health conditions have no impact; or can't work. Four dummy variables were constructed combining the two variables: (1) no long-term health condition, (2) long-term health condition with no limitations, (3) long-term health condition that limits work, and (4) long-term health condition and cannot work. Each variable was included in the regression as a dummy variable.

Smoking Status

The HILDA survey collects data concerning current smoking status using the question '*Do you smoke cigarettes or any other tobacco products?*'. The options for response are (1) No, I have never smoked, (2) No, I no longer smoke, (3) Yes, I smoke daily, (4) Yes, I smoke at least weekly (but not daily), and (5) Yes, I smoke less often than weekly. In the analysis, three dummy variables to represent smoking status were included: ‘non-smoker’ (category 1), ‘previous smoker’ (category 2) and ‘current smoker’ (categories 3–5).

Alcohol consumption

The question used to determine respondent’s consumption of alcohol asked *‘Do you drink alcohol?”* The options for response were (1) I have never drunk alcohol, (2) I no longer drink, (3) Yes, I drink alcohol every day, (4) Yes, I drink alcohol 5 or 6 days per week, (5) Yes, I drink alcohol 3 or 4 days per week, (6) Yes, I drink alcohol 1 or 2 days per week, (7) Yes, I drink alcohol 2 or 3 days per month, and (8) Yes, but only rarely. In the analysis, three dummy variables were created to indicate a ‘non-drinker’ (categories 1 and 2), ‘drinker’ (categories 3–6) and ‘rare drinker’ (categories 6 and 7).

Activity levels

The HILDA survey collects data for each wave concerning the activity levels of participants. The questions ask respondents about how often they participated in moderate activities or exercise (such as walking, bowling or playing golf). Four distinct categories were created to represent (1) No activity, (2) Less than once a week to 2 times a week, (3) 3 times or more a week, or (4) every day.

3.2.5 Missing data

Any missing data for QoL and BMI variables were explored for bias. A dummy variable was constructed to represent that the respondent had a missing value attributed to that variable. The variable was explored through simple regression and a χ^2 test was then used to test if demographic variables impacted on respondents who reported their BMI status or answered the SF-36 questions. The difference between non-responders and responders was not found to be statistically significant.

3.3 Empirical Framework

Both cross-sectional and panel data techniques were used to evaluate the relationship between QoL and BMI. Cross-sectional analysis provides information on the differences between subjects, whereas panel data analysis provides additional information about the changes within subjects over time and controls for unobservable characteristics that are not measurable. The overall goal of the analysis is to predict the expected QoL conditional on BMI, which can be denoted by:

$$\boldsymbol{E(y\,|x) = \beta_0 + \beta_1 x}, \quad where\; y = \beta_0 + \beta_1 x + u \qquad (3\text{-}1)$$

In equation 3-1, the dependent variable y represents QoL and the explanatory variable x represents BMI. The error term u represents factors that affect y other than x (Wooldridge, 2016). The expected outcome of y is conditional on random outcomes (x) from a probability distribution. An assumption needs to be made that u and x are completely unrelated. Additionally, the variance is considered to be homoskedastic, denoted as:

$$\boldsymbol{E(u) = 0} \qquad (3\text{-}2)$$

$$\boldsymbol{var(u|x) = \sigma^2} \qquad (3\text{-}3)$$

These assumptions indicate that the average value of the error term in the population is zero. Any violations of these assumptions require other approaches, such as transformations of the outcome variable, additional or modification of the predictor variables, the estimation of more complex models or the use of non-parametric approaches[28].

3.3.1 Cross-sectional analysis

Using the most recent wave (2015), cross-sectional results were ascertained by running OLS regressions for both males and females with robust errors. Equation 3-4 represents the basic model estimated.

$$\boldsymbol{y_i = \beta_0 + \beta_1 x_i + u_i} \;\; i = 1, \dots, n \qquad (3\text{-}4)$$

In the equation, β_0 is the unknown intercept, x_i represents the characteristics of the individual i (the independent variable), y_i represents the outcome of interest for that particular wave (dependent variable) and u_i is the error term (which contains all other factors that affect y_i other than x_i) (Wooldridge, 2016). Applying this model to estimate the correlation between BMI and QoL, the following models were estimated.

[28] Department of Statistics, University of California: https://www.ics.uci.edu/~sternh/courses/210/slides2new.pdf

$$Model\ 1: \quad \boldsymbol{y_i = \beta_0 + \beta_1 W_i + u_i} \quad i = 1, \dots, n \tag{3-5}$$

$$Model\ 2: \quad \boldsymbol{y_i = \beta_0 + \beta_1 W_i + \beta_2 Z_i + u_i} \quad i = 1, \dots, n \tag{3-6}$$

$$Model\ 3: \quad \boldsymbol{y_i = \beta_0 + \beta_1 W_i + \beta_2 Z_i + \beta_3 X_i + u_i} \quad i = 1, \dots, n \tag{3-7}$$

In these equations, y_i represents the SF-6D score, W_i represents the BMI or BMI group the individual is in, Z_i is the age of each individual i, and X_i are the socioeconomic variables the analysis controls for. First, a simple regression was estimated where only the association between BMI groups and QoL was estimated. Second, the regression was expanded to control for age by using age groups (since QoL decreases over age). The third regression included socioeconomic variables to explain the effect on QoL. Only those individuals that had both a reported BMI and SF-6D score were used in the analysis.

Cross-sectional data are useful to determine the relationship between the variables of interest, but inadequate for differentiating between cause and effect or the sequence of events (Mann, 2003). Some of the bias from cross-sectional data can occur from omitted lagged variables, reverse causation and omitted unobservables. For some data analysis, cross-sectional data is sufficient to answer the research question. In terms of obesity, these data do not provide an indication of patterns in weight changes, persistence of weight status or the onset of obesity-related diseases and comorbidities. It has been shown that changes in weight are more predictive of mortality than static measures of weight; thus, the same outcome may be demonstrated using QoL as the outcome measure (Zheng et al., 2013). Panel data can overcome these limitations by allowing for both a cross-sectional dimension and a time series dimension.

3.3.2 Panel data analysis

Exploiting the panel nature of the HILDA data allows for controlling of variables that cannot be measured or observed and enables one to make inferences on the relationship between BMI and QoL by accounting for individual heterogeneity. The following equation denotes the estimated change in QoL over a one-year time period:

$$\boldsymbol{y_{it} = \alpha z_{it} + \beta x_{it} + \gamma w_{it} + u_i + \varepsilon_{it}} \quad i = 1, \dots, n \quad t = 1, \dots T \tag{3-8}$$

In equation 3-8, y_{it} is the change in QoL, $z_{it}$are time-invariant characteristics, $x_{it}$are time-varying characteristics, i is the individual, t denotes time periods and u_{it} is the between individual error term and ε_{it} is the within-individual error term. The model includes the γ term to represent BMI group (underweight, normal weight, overweight, obese or severely obese).

$$y_{it} = \alpha z_{it} + \beta X_{it} + \gamma W_{it,it-1} + u_i + \varepsilon_{it} \qquad i = 1, \dots, n \quad t = 1 \dots . T \tag{3-9}$$

In equation 3-9, the model was expanded to include the yearly BMI change groups. Each change group (as presented in Section 0) was included in the model as a dummy variable and postestimation commands used to determine the utility decrement for BMI group changes. The model was also expanded to incorporate yearly weight gain/loss groups (as presented in Section 0) to explore absolute body weight percentage changes instead of BMI changes. The baseline QoL was not included in the analyses as the model was estimating the yearly change in weight on QoL over each wave of data.

3.3.3 Econometric analysis

All econometric analyses were conducted using Stata 15. The panel dimension of the data was set using the 'xtset' command with respondent id as the panel id variable and wave number as the time variable, with delta specified as one year. Before analysing the data, a number of tests were performed on the data to determine the appropriate econometric techniques to apply in the analysis.

Specification of dependent variable

The dependent variable in the analysis is the SF-6D, for which regular OLS may not be appropriate, as a linear regression assumes that the errors are homoskedastic. QoL, which is bounded by 0 and 1 (inclusive) [29], tends to be skewed to the left (indicating that most people have QoL values closer to 1). Given the specific nature of health utility data, the choice of econometric techniques is important (Hunger et al., 2012). With this type of data, as the means approach the upper bound, the assumptions about the errors do not hold and heteroskedasticity may hinder the interpretation of the coefficients. Figure 3.4 displays the SF-6D scores for all individuals in wave 15 of HILDA, with a normal distribution overlayed. Wave 15 was used, as it is the most recent wave and the distribution of SF-6D scores is similar across waves.

[29] It is possible to have QoL values less than zero; however, the minimum value in the respondents included in the dataset used was 0.301, and therefore no other model specifications to include values below zero were needed.

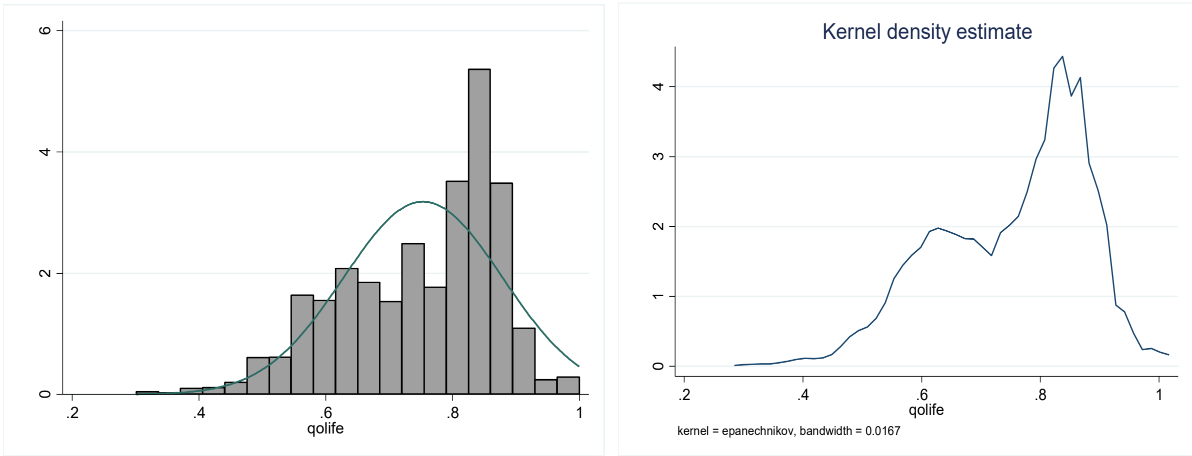


Figure 3.4 Distribution of SF-6D scores (wave 15)

As the histogram and kernel density plot show, the SF-6D is skewed to the left and is truncated at 1. The lowest SF-6D score in the data was 0.301 and the most common QoL score was 0.887; this result is consistent across all waves reporting QoL. Therefore, it is unlikely that the SF-6D score in wave 15 is distributed normally and further model specifications are needed. Other graphical methods to illustrate normality of variables are normal probability (P-P) and quantile-normal (Q-Q) plots (Stata.com). The P-P plot illustrates a standardised normal probability with emphasis on the centre of the distribution. The Q-Q plot illustrates quantiles of SF-6D against quantiles of a normal distribution and emphasises the tails of the distributions (Figure 3.5).

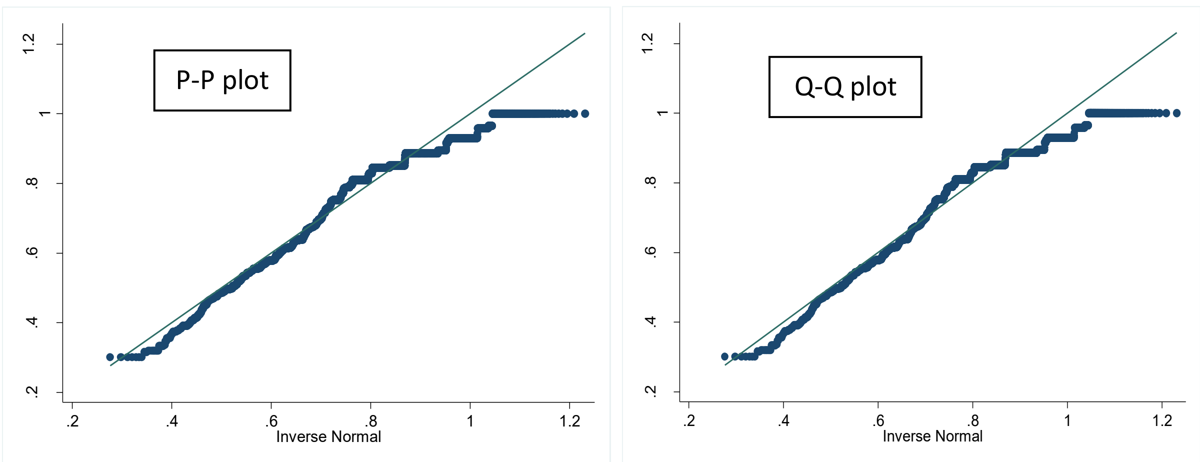


Figure 3.5 Distributional diagnostic plots

The diagnostic plots both indicate that the SF-6D variable is non-normal. The extremes on the ends of the Q-Q plot are far from the normal line. The points in the P-P plot do not match the normal distribution line, indicating non-normality. Although there are tests that can be conducted in Stata to detect non-normality, a deviation that can be clearly spotted using graphs can be more conclusive than the inbuilt numerical tests. Miller (1997) states that 'if a deviation from normality cannot be spotted by eye, it is not worth worrying about' (Stata.com). Further, a Box plot was drawn to illustrate non-normality (see Appendix 8). Numerical tests were carried out for completeness and to further explore the issue of non-normality for pedagogical purposes. The skewness and kurtosis were analysed to determine if the QoL variable rejects the assumption of normality (Table 3.3).

Table 3.3 Summary statistics of SF-6D variable

Statistic	Result	Statistic	Result
N	185500	Range	0.699
mean	0.761	Sd	0.124
median	0.793	Variance	0.153
sum	141084	se (mean)	0.0003
max	1	Skewness	–0.606
min	0.301	Kurtosis	2.721

The skewness estimate of –0.606 indicates that the data is skewed to the left and different than zero (which is the skewness of the normal distribution). The kurtosis value of 2.721 is close to 3, which indicates normality. The numerical tests in Stata to test for normality (such as the Shapiro-Wilk and Shapiro-Francia test) are recommended for datasets with a small N (<2,000 and <5,000). A Jarque-Bera test can be conducted as it performs better on large number of observations. A user-written Stata code was installed to conduct the Jarque-Bera test in Stata. Based on the visual tools, it appears that the SF-6D variable does not fit a normal distribution. Alternative regression models in addition to a simple linear regression were explored that consider the non-normality of the utility data.

Regression models

The most commonly used analysis techniques when health utility is the dependent variable are beta regressions, OLS with robust errors, tobit models and, less commonly, latent class models and proportional odds ordinal logistic regressions. A regular linear regression assumes that the residuals are normally distributed, which may not hold given the distribution of the SF-6D (Pullenayegum et al., 2010). Other methods include converting dependent variables that were utility values into quintiles, tertiles or dichotomised (<100 and =100). One of the more frequent analytic solutions is to use a beta regression when utility data is the dependent variable. Beta regressions are commonly used when analysing proportions. However, when the variable includes a large proportion of ones, a beta regression is not appropriate.[30] A zero/one inflated beta model (which allows values of 0 and 1) is one method for using a beta regression with utility data. A similar method is to transform the ones in the data to a value slightly less than one using the formula $y' = (y*(N-1) + 0.5)/N$. Stata guides suggest the use of generalised linear models instead of 'winsorizing' the ones to an arbitrary value (Baum, 2008). A comparison of multiple analysis methods has shown that tobit and CLAD models lead to bias when specifying data to be bounded above one, and are therefore not appropriate for calculating QALYs (Pullenayegum et al., 2010). Overall there are many suggested regression models for cross-sectional data, however longitudinal research methods are less developed (Hunger et al., 2012). Table 3.4 summarises the models used for health-related QoL data and the commands used in Stata and the corresponding commands used in panel data with QoL data.

Table 3.4 Health-related quality of life models

Model	Specifications	Stata command	Stata command panel data
Tobit	Values censored at 1	Tobit	metobit
Beta	Bounded at 1	betafit betareg[1]	beta glmm
Beta (transformed 1s)	Bounded at 1	Betafit	beta glmm
Logit transformed	Bounded at 1	regress (logit_SF-6D)	xtlogit
Zero/one inflated beta	0s and 1s represent distinct processes	zoib[2]	zoib (cluster)
Latent class	Distribution is bimodal	Gllamm	
OLS (robust errors)		regress, [robust]	xtreg
Fractional logit	0s and 1s occur through the same process as the other proportions	glm family (binomial) link(logit) vce (robust)	xtgee
Fractional response regression	Greater than or equal to 0, less than or equal to 1	fracreg[1] (logit)	xtgee
CLAD	Values censored at 1	CLAD	

[1]*New commands added to STATA 15; CLAD: censored least absolute deviations*
[2]*The zero/one inflated beta 'zoib' is a user written command: http://www.maartenbuis.nl/software/zoib.html*

Based on the evidence and Stata recommendations, the models tested were the beta-adjusted regression, an OLS regression with robust standard errors and a fractional logit model (Papke & Wooldridge, 1996). OLS with robust errors can result in unbiased regression coefficients; however, the estimates may not be as precise as with other analysis methods (Institute for

[30] Betareg in Stata: https://www.stata.com/manuals/rbetareg.pdf

Digital Research and Education, 2017). A fractional response regression analysis using a recently added Stata command (fracreg) was used as a comparison to the other models. The following four models were evaluated:

- Model 1: Beta regression (ones changed to 0.995)
- Model 2: Linear OLS with robust standard errors
- Model 3: Fractional response model with family (binomial) link(logit) vce(robust)
- Model 4: Fractional logit using GLM with family (binomial) link(logit) vce(robust)

Fractional responses models involve outcomes that are between zero and one, and fit data on a continuous interval between zero to one. In Stata the 'fracreg' command is executed using probit, logit, or heteroskedastic probit. The command 'betareg' is also used for fractional responses but excludes zeros and ones.[31]

Panel data regression models

Using ordinary least squares (OLS) regression methods for longitudinal data is not appropriate as the designs of these surveys normally have correlated observations (Hunger et al., 2012). OLS may produce imprecise standard errors and the corresponding p-values for the regression coefficients. Currently many of the studies with health-related QoL as the dependent variable are analysed using change scores, ANOVA and linear mixed models (Hunger et al., 2012). Generalised estimating equations (GEEs) with linear regressions and adjusted errors were also commonly used in the more recent studies that included QoL as a continuous outcome variable (Döring et al., 2015; Milder et al., 2014; Verkleij et al., 2013). The following models were estimated, and the resulting coefficients and the model diagnostics compared:

- Model 1: Linear regression with fixed effects
- Model 2: Linear regression with random effects
- Model 3: Generalised estimation equation with family(binomial), link(logit), corr(independent), vce(robust)
- Model 4: GLM with link(logit), family(binomial) vce(robust) cluster(id)

[31] Fractional outcome regression: http://www.stata.com/new-in-stata/fractional-outcome-models/

Fixed effects vs. Random effects

A Hausman[32] test was also conducted to validate the use of a random effects model. The Hausman test is run by storing both fixed and random effects estimates and the null hypothesis compares the 'within-respondent' and 'between-respondent' factors. If the resulting χ^2 test statistic is large, we can reject the null hypothesis that using a random effects model is appropriate.

Generalised estimation equations (GEEs)

GEE models for panel data can be useful to explore BMI change groups and weight change groups. A variety of models can be used with GEEs (linear, logistic, poisson) and use robust standard errors to allow for clustering in the data. Papke and Wooldridge (2008) recommend the use of 'xtgee' or 'glm' for balanced panel data. The xtgee command returns the same result as an 'xtreg' with random effects. Generalised estimating equations account for both the within-subject and the within-cluster correlations and allow for time-varying covariates. GEEs also allow for a range of correlations structures and require a large number of clusters (i.e., subjects) (Baum, 2008). All the longitudinal models run using a GEE framework were specified with family(binomial), link(logit), corr(independent), i(id) vce(robust) with the 'id' specification indicating each respondent in the survey. The following analyses were conducted:

- Analysis 1: BMI categories for males and females
- Analysis 2: BMI category movements
- Analysis 3: Weight change groups with continuous BMI
- Analysis 4: PCS and MCS summary scores

The specification of a binomial distribution and a link logit is a strategy proposed by Papke and Wooldridge (1996) for handling proportions data where zeros and ones may appear (Baum 2008). The dependent variables in the analyses (SF-6D, PCS, MCS scores) are bounded and include 1 and, therefore, the variance will be maximised with a mean of 0.5 using these models.

Exploration of normality of residuals

[32] The Hausman test is a generally accepted way of choosing between fixed and random effects when using panel data. Statistically a fixed effects model gives more consistent results but may not be the most efficient model to run. A random effects model will provide better p-values as they are a more efficient estimator. http://dss.princeton.edu/online_help/stats_packages/stata/panel.htm

The appropriateness of a linear regression assumes that the residuals are independent and distributed normally. Ensuring that each of the covariates used in the regression is distributed normally is not required to obtain estimates of the coefficients.

Tests in Stata for each model run were conducted by using post-estimation commands and looking at the distribution of the residuals. A Jarque-Bera[33] test for normality was also run on the residuals to test the hypothesis that the residuals are distributed normally (Park, 2015). The Jarque-Bera test is a useful method to test the normality for larger samples greater than 2,000 observations.

Subpopulations

Within the regression, the 'subpop' command was used in lieu of 'if' statements to specify the subpopulations in the analysis. This was employed to estimate the correct standard errors. The subpop command was used to run separate regressions for gender. Conditional 'if' statements at the end of the regression were used to specify wave 15 and adults 18 years and older. If these are added into the subpopulation specification the model overestimates the population, as it runs the model on all the missing data from that is excluded from the subpopulation specified.

3.3.4 Gender specification

The models were all run for both males and females, as there are distinct differences between genders in terms of QoL for BMI states. A preliminary test was conducted exploring the BMI groups on QoL with an interaction for gender, resulting in highly statistically significant differences between males and females in each BMI category.

3.3.5 Complex survey design

The HILDA survey was conducted using a complex survey design, as opposed to simple random sampling (which normally is very expensive to collect). The HILDA survey was collected using census collection districts and dwellings systematically chosen and all individuals within a household chosen. Due to the complex survey, the clustering and stratification need to be considered by adjusting the estimates of variance to be confident in the results.

[33] The Jarque-Bera test is a test for normality calculated from the sample skewness and kurtosis compared to a chi-squared distribution.

3.3.6 Sample weights

Statistical software (such as Stata) assumes random sampling when analysing the data. Without considering the survey design, the point estimates and standard errors will be incorrectly estimated (Institute for Digital Research and Education, 2006). Sampling weights were applied in the analysis to allow for a more realistic representation of the Australian population. The weights are used to adjust for attrition to the sample, which is not random. The reinterview rate of the HILDA survey is lower among persons aged between 15 and 24, born in a non-English speaking country, of Aboriginal or Torres Strait Islander descent, single, unemployed or working in low-skilled occupations (Watson, 2012). The sampling weights were defined as the inverse sampling probability for each participant and are supplied with each wave of data. HILDA provides both cross-sectional and longitudinal weights.

In Stata, both the ‘svy’ command, which uses a Taylor series method, and the ‘svy jackknife’ command, which uses a replicate weight method, were used to weight the sample. The HILDA data provides cross-sectional weights, longitudinal and self-completion questionnaire weights for each wave. The strata variable was based on household member characteristics and the cluster variable by person identifiers.

Standard errors

The complex nature of the HILDA survey needs to be accounted for when estimating any standard errors. The data is clustered in stratified areas and unequally weighted (Summerfield et al., 2017). The HILDA manual suggests using the Taylor Series linearisation method or the Jackknife replicate method for calculating the appropriate standard errors (Hayes, 2008). In Stata, the ‘svy’ command in recommended for complex survey designs.

3.4 Results: Summary statistics

Summary statistics were calculated to provide an overview of each variable used in the analysis. Table 3.5 presents the summary statistics for respondents using the latest wave of data (wave 15). The mean values of BMI and SF-6D score are also reported by different sociodemographic and economic characteristics.

In general, QoL decreases with age and BMI tends to increase with age up to 75 years. Those with the lowest BMI tend to have the highest OECD income, to not have any long-term health conditions, to be married or living with a partner, to have a degree or higher qualification, and to be employed or students. A similar trend is seen with average QoL across these demographics.

The summary statistics reporting the proportion of individuals in each BMI category, height, weight and BMI were also compared to the 2011–2012 Australian Health Survey for validation of population representativeness. The Australian Health Survey is a cross-sectional survey conducted by the ABS and includes national statistics on long-term illnesses; mental well-being, injuries; consultations with doctors and other health professionals; and health risk factors (including alcohol consumption, smoking, exercise, BMI and dietary practices). In total, 20,788 persons (who were usual residents of private dwellings in urban and rural areas of Australia) completed questionnaires by personal interview.[34] Physical measurements were obtained for all persons aged two and over who agreed to the measurements being taken (excluding pregnant women)[35].

Table 3.6 presents a summary of the proportion of respondents in each BMI category for waves 6 to 13 of the HILDA data. The proportion of respondents in each BMI category compared to the 2011–2012 AHS is also presented.

[34] ABS Australian Health Survey: http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/9E22DA7218BCCADACA257B8D00229EA5? opendocument

[35] Body mass and physical measurements: http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/4363.0~2014-15~Main%20Features~Body%20mass%20and%20physical%20measurements~43

Table 3.5 Summary statistics of respondents in HILDA wave 15

	Respondents	%	Mean BMI	Mean SF-6D
Male	7,898	47.2%	27.35	0.765
Female	8,849	52.8%	26.89	0.744
Age				
15-24	2,278	13.6%	24.9	0.773
25-34	3,266	19.5%	26.4	0.779
35-44	2,676	16.0%	27.5	0.767
45-54	2,851	17.0%	27.9	0.757
55-64	2,492	14.9%	28.1	0.740
65-74	1,884	11.3%	28.0	0.731
75+	1,300	7.8%	26.3	0.684
Marital Status				
Married/living together	10,305	61.5%	27.3	0.763
Separated/divorced/widow	3,027	18.1%	27.8	0.713
Single	4,413	20.4%	26.0	0.759
Remoteness				
Metropolitan area	14,631	87.4%	27.0	0.755
Non-metropolitan area	2,115	12.6%	27.9	0.744
Employment status				
Employee	9,090	54.3%	26.8	0.782
Self-employed	1,574	9.4%	26.9	0.777
Unemployed	716	4.3%	27.1	0.728
Unpaid housework	1,107	6.6%	27.7	0.727
Retired	3,001	17.9%	27.4	0.708
Student	299	1.8%	24.9	0.752
Other	960	5.7%	29.1	0.636
Education				
Degree or higher	4,415	26.4%	26.0	0.777
Year 12, certificate, diploma	8,244	49.2%	27.3	0.757
Year 11 or below	4,088	24.4%	28.2	0.719
Long-term health condition (LTHC)				
No LTHC	11,786	70.5%	26.5	0.791
LTHC – limits work	3,217	19.2%	28.9	0.636
LTCH – no limitations	1,456	8.7%	27.8	0.737
LTCH - can’t work	263	1.6%	29.1	0.563
OECD equivalised income				
OECD quintile 1 (lowest)	3,354	20.0%	27.6	0.694
OECD quintile 2	3,307	19.8%	27.4	0.740
OECD quintile 3	3,304	19.7%	27.2	0.762
OECD quintile 4	3,366	20.1%	26.9	0.778
OECD quintile 5 (highest)	3,416	20.4%	26.4	0.788
Smoking				
Non-smoker	12,019	82.3%	27.1^	0.760
Smoker	2,587	17.7%	27.1^	0.724
Drinking				
Non-drinker	6,057	41.4%	27.6	0.732
Drinker	8,560	58.6%	26.7	0.769
Activity				
No activity	1,775	12.1%	29.0	0.663
2	2,536	17.3%	28.2	0.732
3	5,659	38.6%	27.0	0.761
4	4,692	32.0%	26.0	0.790

^ p-value was not significant, indicating that the groups were not statistically significantly different from each other. All other groups differed by mean BMI, mean SF-6D and proportion depressed.

Table 3.6 Proportion of subjects by BMI weight category by wave (aged 18 and over) AHS[b]

	HILDA Survey										AHS[b]
	Wave 6 N=10,449	**Wave 7 N=10,141**	**Wave 8 N=9,956**	**Wave 9 N=10,391**	**Wave 10 N=10,708**	**Wave 11[a] N=13,837**	**Wave 12 N=13,972**	**Wave 13 N=14,061**	**Wave 14 N=14,108**	**Wave 15 N=13,974**	**2014-2015 N=17,733**
Weight (kg)											
Males (mean)	84.4	84.4	84.5	85.2	85.4	84.5	85.3	85.0	85.5	85.9	86.4 kg
Females (mean)	69.7	69.8	70.2	70.7	71.1	70.3	70.7	71.3	71.1	71.4	71.4 kg
Height (cm)											
Males (mean)	177.4	177.3	177.5	177.5	177.3	177.3	177.3	177.4	177.4	177.5	176.1 cm
Females (mean)	163.3	163.3	163.5	163.5	163.6	163.4	163.5	163.5	163.6	163.7	162.2 cm
BMI											
Males	26.8	26.8	26.8	27.0	27.1	26.9	27.1	27.0	27.1	27.2	27.8
Females	26.2	26.2	26.3	26.5	26.6	26.4	26.4	26.7	26.5	26.7	27.2
Males											
Underweight	1.1%	1.3%	1.1%	1.3%	1.5%	1.6%	1.4%	1.7%	1.8%	1.5%	1.2%
Normal weight	35.8%	35.4%	35.0%	34.5%	33.6%	35.1%	33.2%	34.7%	33.6%	34.5%	28.1%
Overweight	40.9%	41.5%	41.9%	41.2%	41.4%	41.7%	42.7%	41.4%	41.6%	40.2%	42.4%
Obese	17.3%	16.7%	17.1%	17.2%	16.7%	15.9%	16.7%	16.0%	16.1%	16.1%	26.2%
Severely Obese	5.0%	5.1%	4.9%	5.8%	6.8%	5.8%	6.0%	6.2%	6.9%	7.8%	2.1%
Females											
Underweight	3.9%	3.7%	3.5%	3.1%	2.9%	3.7%	3.4%	3.7%	3.3%	3.4%	2.1%
Normal weight	45.7%	45.4%	44.2%	44.2%	43.0%	45.1%	45.9%	43.5%	44.7%	44.3%	41.7%
Overweight	28.6%	29.1%	29.8%	29.2%	30.1%	27.6%	27.2%	27.6%	28.3%	27.2%	28.8%
Obese	14.1%	14.2%	14.5%	14.6%	14.9%	15.1%	14.7%	15.3%	13.9%	14.0%	23.2%
Severely obese	7.7%	7.7%	8.1%	8.9%	9.1%	8.6%	8.9%	9.9%	9.9%	11.0%	4.2%
Persons											
Underweight	2.5%	2.5%	2.3%	2.2%	2.2%	2.6%	2.4%	2.7%	2.6%	2.4%	1.6%
Normal weight	40.8%	40.4%	39.6%	39.4%	38.4%	40.1%	39.5%	39.1%	39.2%	39.4%	35.0%
Overweight	34.7%	35.3%	35.8%	35.2%	35.7%	34.6%	34.9%	34.4%	34.9%	33.7%	35.5%
Obese	15.7%	15.5%	15.8%	15.9%	15.8%	15.5%	15.7%	15.7%	15.0%	15.0%	24.6%
Severely obese	6.3%	6.4%	6.5%	7.4%	7.9%	7.2%	7.4%	8.1%	8.4%	9.4%	3.2%

[a]*Wave 11 includes the top-up sample of 2000 households added to the HILDA survey*
[b]*All persons had height and weight measured. A 'hot decking' imputation method was used for the 26.8% of non-responders measured. Source: Australian Bureau of Statistics, 2015.*

The average height, weight and BMI calculated from the HILDA data appear to correspond to those of the AHS data. Over the 10 waves, both weight and BMI have changed over time (given it is a panel we would expect height to remain relatively constant with minor fluctuation due to missing data). The BMI group classifications calculated from HILDA differ significantly from the AHS data. The severely obese groups appear to be over-represented and the obese category under-represented.

Table 3.7 summarises the QoL measures by the SF-6D utility score, SF-36 summary measures of physical and mental health and the average scores in the eight SF-36 health dimensions. The SF-6D score is a preference-based index between 0 and 1 (see Section 3.2.2) and the SF-36 summary measures (PCS/MCS) and dimension scores range from 0 to 100, with a higher score indicating a better health status.

Table 3.7 Quality of life summary statistics (wave 15)

	PCS	MCS	PF	RP	BP	GH	VT	SF	RE	MH	SF-6D
Males											
Underweight	42.68	44.15	70.4	47.4	62.2	55.3	53.2	68.1	54.4	69.0	0.676
Normal weight	51.04	49.72	86.2	84.3	78.2	71.4	64.2	84.8	86.4	75.8	0.782
Overweight	49.87	49.17	85.1	82.2	74.2	67.7	61.8	83.5	85.2	75.0	0.767
Obese	47.26	47.91	80.2	76.3	67.6	61.3	58.0	79.3	80.0	73.1	0.739
Severely obese	44.88	47.07	74.2	68.8	65.7	55.5	54.6	75.8	78.1	70.9	0.715
Females											
Underweight	49.93	45.74	80.5	77.9	75.8	65.3	56.5	78.4	81.3	67.5	0.731
Normal weight	51.10	48.26	85.8	82.5	76.7	71.9	60.1	83.6	83.8	73.6	0.768
Overweight	48.05	48.20	81.8	74.6	69.6	66.8	57.6	80.1	81.6	73.4	0.744
Obese	45.58	46.90	75.7	69.0	64.1	61.8	53.4	75.9	76.6	71.2	0.717
Severely obese	42.80	46.33	68.9	63.3	59.1	56.0	50.7	73.2	73.4	69.2	0.695

Abbreviations: PCS – physical component score, MCS – mental component score, PF – physical functioning, RP – role physical, BP – bodily pain, GH – general health, VT – vitality, SF – social functioning, RE – role emotional, MH – mental health

In general, the higher weight categories were associated with lower levels of overall QoL. When comparing the SF-36 by health domains, the higher weight categories display higher PCS and MCS scores, indicating a worsening in physical and mental functioning. Compared to the normal weight category, the overweight categories are associated with much lower physical QoL and slightly lower mental QoL.

3.4.1 Weight change groups

The percentage of respondents for each weight change group were calculated for each wave. Approximately 70% of respondents remained within 5% of their initial body weight over the 10 waves (Table 3.8).

Table 3.8 Percentage of survey respondents by yearly weight change (waves 7-15)

	7	8	9	10	11	12	13	14	15
Heavy gainers	7.4%	6.6%	6.9%	6.2%	6.1%	6.2%	6.6%	6.3%	6.3%
Gainers	12.2%	12.3%	11.9%	11.6%	11.0%	11.5%	11.7%	11.3%	11.5%
Stable	67.6%	68.5%	68.9%	70.0%	69.5%	68.9%	68.7%	69.4%	69.6%
Losers	8.5%	8.5%	8.5%	8.2%	9.1%	8.9%	8.8%	8.4%	8.4%
Heavy losers	4.3%	4.0%	3.8%	4.0%	4.2%	4.5%	4.2%	4.6%	4.2%

Heavy gainers: ≥ 10% of body weight; gainers: ≥ 5% and < 10% of body weight; stable: ≥-5% and ≤ 5% of body weight; losers: ≥- 5% and < -10% of body weight; heavy losers: > -10% of body weight

3.5 Results: Cross-Sectional Analysis

Using wave 15 of the HILDA survey, it is estimated that 58.1% of the Australian population are considered overweight or obese (33.7% and 24.4% respectively). Overall, higher SF-6D scores were reported for the normal weight category compared to the other weight categories. Figure 3.6 presents the average QoL for each BMI category by gender (without controlling for any sociodemographic or economic variables).

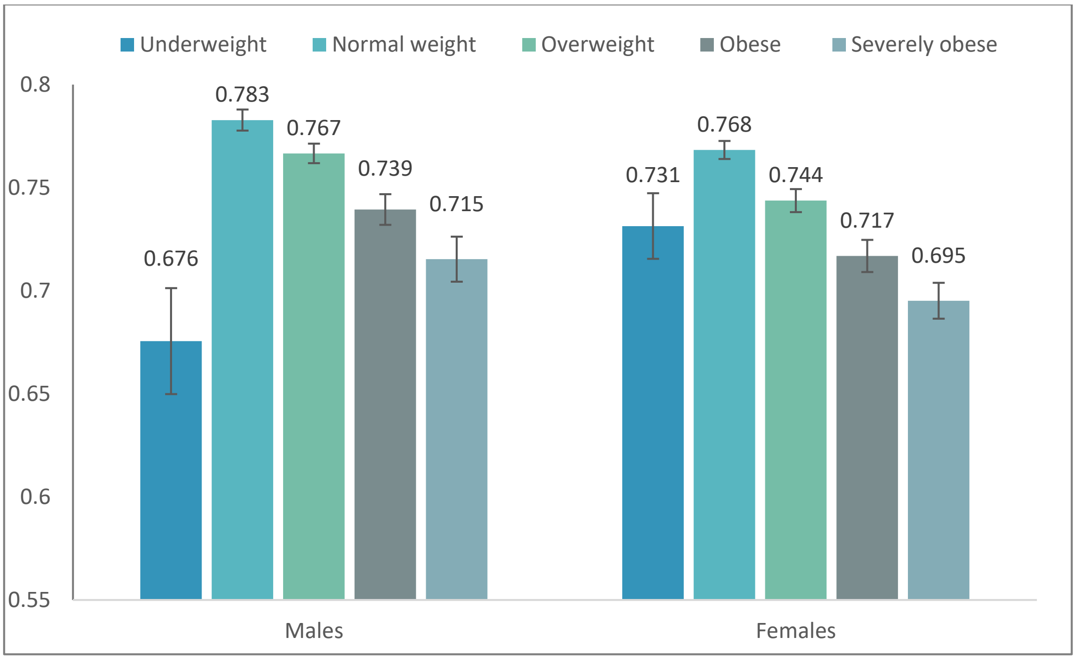


Figure 3.6 Average QoL by BMI category (wave 15)

As can be seen, deviations from the normal weight category result in reductions in QoL. The highest QoL is associated with being in a normal weight category for both males and females. Males experience worse QoL in the underweight category compared to being obese, whereas being obese is associated with the worst QoL for females.

The results of the four models are presented in Table 3.9. All models were controlled for age, education, income, remoteness, marital status, employment status, smoking status, alcohol consumption and long-term health conditions. The reference group was compared to a normal weight individual in wave 15.

Table 3.9 Results of cross-sectional models

	Model 1 OLS robust errors		Model 2 Beta regression		Model 3 Fractional response		Model 4 GLM	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Underweight	–0.042**	–0.017	–0.224**	–0.083*	–0.224**	–0.092*	–0.224**	–0.092*
Normal weight	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Overweight	–0.010**	–0.015***	–0.059**	–0.091***	–0.058**	–0.086***	–0.590**	–0.086***
Obese	–0.028***	–0.025***	–0.179***	–0.140***	–0.160***	0.137***	–0.160***	–0.137***
Severely obese	–0.041***	–0.039***	–0.246***	–0.214***	–0.223***	–0.203***	–0.223***	–0.203***
R^2	0.2982	0.3094	–	–	0.0217	0.0216	–	–
LL	4273.25	4625.42	4608.47	4957.67	–3344.00	–3980.01	–2349.79	–2706.29
AIC	–10715.48	–11787.73	–11062.23	–12115.2	6785.11	7854.44	4765.59	5478.57
BIC	–10492.72	–11561.42	–10832.72	–11882.03	7007.86	8080.75	4988.34	5704.88

Controlled for age, education, income, remoteness, marital status, employment status, smoker, drinker, long-term health conditions. Statistically significant at p<0.05, p<0.01** and p<0.001****

The AIC and BIC estimates from the four different models cannot be compared directly, as the scales of the dependent variable in the models are different. Therefore, picking the smallest AIC value does not necessarily indicate a better model fit when the dependent data has been transformed in the models. Given that the model fit was similar between the models and the easier interpretation of a linear model, an OLS with robust standard errors was further used to compare BMI and QoL in wave 15. Furthermore, an analysis of the predicted values demonstrated that the estimates of QoL did not exceed 1 or fall below 0, which indicates that the model is appropriate for estimating the relationship between BMI and QoL. Hunger et al. (2012) similarly found that a linear regression did not predict any values greater than one and performed as well as the beta regression model. Table 3.10 demonstrates the cross-sectional associations for both males and females with regards to QoL and BMI groups. Post-estimation commands were conducted to make multiple comparison across the five weight groups to compare which of the estimated coefficients were significantly different from the other weight groups. A Bonferroni adjustment was included to take into account the significance of multiple comparisons.

Table 3.10 Cross-sectional associations

	Underweight	Normal weight	Overweight	Obese	Severely obese
Males					
Underweight	-	0.042**	0.033*	0.015	0.002
Normal weight	–0.042**	–	–0.010**	–0.028***	–0.041***
Overweight	–0.033*	0.010**	–	–0.018***	–0.031***
Obese	–0.015	0.028***	0.018***	–	–0.013*
Severely obese	–0.002	0.040***	0.031***	0.013*	–
Females					
Underweight	–	0.017*	0.001	–0.008	–0.022*
Normal weight	–0.017	–	–0.015***	–0.025***	–0.039***
Overweight	–0.001	0.015***	–	–0.010*	–0.024***
Obese	0.008	0.025***	0.010*	–	–0.014**
Severely obese	0.022*	0.039***	0.024***	0.014**	–

Statistically significant at p<0.05, p<0.01** and p<0.001****

These results indicate that being normal weight is associated with higher QoL and the relationship is statistically significantly different from the other four weight categories in males; however, there is no significant difference between normal weight and underweight females. The largest decrements to QoL are observed in movements away from normal weight to severely obese. This table does not indicate whether the changes from one BMI group to another will cause these QoL decrements, it only demonstrates the association between BMI groups and QoL.

Table 3.11 presents these results from the final cross-section models using OLS with robust standard errors. In Model 1, a simple model was run including just QoL and BMI, compared to normal weight for all respondents. Being male and any BMI other than normal was associated with lower QoL. In Model 2, with separate models run for males and females, all other BMI categories (compared to normal weight) were associated with lower QoL and are statistically significant; however, being in the underweight category had a more significant impact for males. In Model 3, an individual's age was introduced into the model, given that, in general, increasing age is associated with lower QoL. Once age is controlled for, the association between QoL and being overweight in males was not as significant. All other associations remain consistent with Model 2. These results support the existing literature that demonstrates a negative association with BMI for movements away from a healthy weight.

In Model 4, the base case is a male/female of normal weight, married or living with a partner in a metropolitan area, employed with a degree or higher with no long-term health condition and no history of smoking. The results demonstrate that lower QoL is associated with being obese and severely obese in both males and females, being underweight in males, and being overweight in females. Controlling for socioeconomic and demographic variables reveals that increased age and the presence of a long-term health condition accounts for most of this QoL reduction. As well, those with the lowest incomes, current smokers and divorced/separated or widowed have a lower QoL.

Table 3.11 Cross-sectional results

	Model 1	**Model 2**		**Model 3**		**Model 4**	
		Males	**Females**	**Males**	**Females**	**Males**	**Females**
Male	0.018***						
Underweight	–0.056**	–0.108**	–0.036*	–0.110**	–0.038*	–0.049**	–0.025
Overweight	–0.020***	–0.016**	–0.024***	–0.011*	–0.020***	–0.012*	–0.015***
Obese	–0.047***	–0.043***	–0.051***	–0.037***	–0.046***	–0.031***	–0.032***
Severely obese	–0.071***	–0.067***	–0.073***	–0.063***	–0.071***	–0.036***	–0.037***
Age 25–34				–0.007	0.003	0.025*	–0.017
Age 35–44				–0.018	0.008	0.012	–0.009
Age 45–54				–0.023***	–0.005**	0.002	0.000
Age 55–64				–0.038***	–0.259**	0.007	–0.002
Age 65–74				–0.050***	–0.027***	0.024*	0.016
Age 75+				–0.091***	–0.087***	0.004	–0.004
Year12, cert/diploma						0.007	0.002
Year11 and below						0.007	–0.001
OECD income 1						–0.021**	–0.019**
OECD income 2						–0.011	–0.015
OECD income 3						–0.003	–0.013
OECD income 5						0.009	0.006
Self–employed						0.004	0.001
Unemployed						–0.013	–0.018
Unpaid housework						–0.004	–0.015
Retired						–0.013	–0.078
Student						–0.023	–0.004
Other						–0.043***	–0.040***
Non-metro area						0.001	0.001
Sep/div/widowed						–0.018***	–0.017**
Single						–0.010	–0.000
LTHC – no limitations						–0.126***	–0.132***
LTHC – limits work						–0.040***	–0.050***
LTHC– can't work						–0.172***	–0.184***
Smoker						–0.002***	–0.010***
Previous smoker						0.002	0.004
Non-drinker						–0.004	–0.026***
Drinker						0.002	0.008
_cons	0.767***	0.783***	0.768***	0.805***	0.778***	0.819***	0.831***
R^2	0.0392	0.0332	0.0393	0.0665	0.0775	0.2832	0.3034
LL	8997.15	4227.99	4529.80	4227.99	4529.80	4204.78	4488.54
AIC	–17982.3	–8659.35	–9331.81	–8868.27	–9604.61	–10424.93	–11427.41
BIC	–17937.3	–8625.60	–9297.52	–8794.02	–9529.17	–10202.5	–11201.43

Statistically significant at p<0.05, p<0.01** and p<0.001****

Another option is the use a pooled analysis in which each wave of data for the respondent is considered a data point; however, this does not give consistent estimates of the covariates and the errors are likely to be correlated over time for a given respondent. The next section will discuss the panel data methods used to analyse the relationship between BMI and QoL.

3.6 Results: Longitudinal analysis

The results from the longitudinal analysis using all the waves demonstrate similar results to the cross-sectional analysis with the BMI categories (for all four models run). Table 3.12 summarises the regression estimated coefficients for the BMI categories with normal weight as the reference group.

Table 3.12 Results of longitudinal models

	Model 1 Fixed effects		**Model 2 Random effects[36]**		**Model 3 GEE (independent)**		**Model 4 GEE (exchangeable)**	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Underweight	–0.014*	–0.010**	–0.019***	–0.012***	–0.162***	–0.080***	–0.107***	–0.068***
Normal weight	–	–	–	–	–	–	–	–
Overweight	0.003	–0.004**	–0.001	–0.007***	–0.034***	–0.045***	–0.005	–0.038***
Obese	–0.003	–0.016***	–0.011***	–0.021***	–0.108***	–0.108***	–0.067***	–0.111***
Severely obese	–0.015***	–0.028***	–0.027***	–0.036***	–0.171***	–0.176***	–0.149***	–0.186***
R^2								
LL	71111.1	77855.6	56244.1	61514.5				
AIC	–142158.3	–155647.2	–112418.2	–122958.9				
BIC	–141873.1	–155358.7	–112106.3	–122643.3				

Controlled for age, education, income, remoteness, marital status, employment status, smoker, drinker, long-term health conditions. Statistically significant at p<0.05, p<0.01** and p<0.001***.*

The results from the fixed and random effects models indicate that males who are overweight have higher QoL than normal weight males; these results are also consistent with the literature. This could reflect the BMI's inability to distinguish between muscle mass and fat, which to these individuals would be considered normal weight. The largest decrement in QoL based on the fixed and random effects models were in those individuals who were severely obese. In all the models, the presence of a long-term health condition (whether that limited work or not) produced a significant reduction in QoL. In addition, reductions in QoL were seen in those who were unemployed, retired, divorced or separated.

[36] To calculate the AIC and BIC for the random effects model, a maximum likelihood model was run, which estimates similar coefficients. The reported standard errors are those from the random effects model clustered around id.

Random vs Fixed Effects

Comparing the two linear models using a Hausman test, a fixed effects model was deemed more appropriate as the variation across individuals is not assumed to be random and is correlated with the predictor or individual variables included in the model.

Fixed effects are appropriate for analysing the impact of variables that vary over time; in this case we are interested in weight and QoL, which do vary with time. A fixed effects model allows for each respondent to have individual characteristics that influence the predictor variables and removes those variables that are time-invariant so the net effect of the predictors on the outcome variable can be assessed. Other advantages of the fixed effects model are that individual specific or time effects can be correlated with the explanatory variables and the model does not require correlation patterns to be specified (Hsiao, 2007).

Time fixed effects

With panel data, it may be appropriate to test for time-fixed effects as it is possible that the variations in QoL may be explained by overall time trends. The 'testparm' command was used in Stata and resulted in a rejection of the null that all waves are jointly equal to zero. Accordingly, the final models incorporated dummy variables for each wave in the data. By including each wave in the model, any omitted variables that may be common to all respondents but vary over time are controlled for (de Haan, n.d.).

Heteroskedasticity

A modified Wald test in Stata was conducted to test for groupwise heteroskedasticity in the model, which may cause the standard errors of the coefficients to be biased if not accounted for. The 'xttest3' command was performed in Stata and resulted in a rejection of the null (constant variance) and the conclusion that the data are heteroskedastic. Consequently, a further specification of the model was the use the robust standard errors command, which controls for heteroskedasticity.

3.6.1 Analysis 1: BMI categories

The final models in Table 3.13 include the time effects by wave and robust standard errors. A fixed effects model was estimated (as the tests confirmed there was individual heterogeneity that needed to be controlled for). A GEE model with an exchangeable correlation structure was also estimated to compare results.

Table 3.13 Longitudinal Models

	Fixed Effects				GEE			
	Males	**se**	**Females**	**se**	**Males**	**se**	**Females**	**se**
Underweight	–0.014**	0.005	–0.009**	0.003	-0.100***	0.024	-0.061***	0.015
Overweight	0.004***	0.001	–0.003*	0.001	-0.001	0.007	-0.033****	0.006
Obese	0.0002	0.002	–0.012***	0.002	-0.051***	0.009	-0.092***	0.008
Severely obese	–0.008*	0.003	–0.022***	0.003	-0.112***	0.014	-0.153***	0.011
Age 25–34	–0.004	0.004	–0.008*	0.004	0.084***	0.014	-0.009	0.013
Age 35–44	0.000	0.003	–0.004	0.002	0.042***	0.010	-0.009	0.010
Age 45–54	0.002	0.002	–0.002	0.002	-0.032**	0.010	-0.037***	0.009
Age 55–64	0.005	0.003	0.003	0.003	-0.028*	0.012	-0.021	0.011
Age 65–74	0.010*	0.005	0.008	0.004	-0.013	0.015	-0.006	0.013
Age 75+	–0.003	0.006	–0.005	0.006	-0.095***	0.018	-0.088***	0.016
Year 12/certificate/diploma	0.003	0.004	–0.002	0.004	-0.028*	0.011	-0.009	0.010
Year 11 and below	0.006	0.006	–0.005	0.005	-0.062***	0.013	-0.029*	0.012
OECD income 1	–0.002	0.002	–0.002	0.002	-0.062***	0.009	-0.061***	0.008
OECD income 2	0.000	0.002	–0.002	0.002	-0.029***	0.008	-0.035***	0.007
OECD income 3	0.001	0.001	–0.002	0.001	-0.009	0.007	-0.022***	0.007
OECD income 5	0.001	0.001	0.002	0.001	0.024***	0.007	0.018**	0.007
Self-employed	–0.003	0.002	–0.002	0.002	-0.021*	0.010	-0.016	0.011
Unemployed	–0.010***	0.003	–0.001	0.003	-0.091***	0.014	-0.053***	0.013
Unpaid housework	–0.018***	0.005	–0.009***	0.002	-0.130***	0.026	-0.068***	0.008
Retired	–0.011***	0.002	–0.010***	0.002	-0.112***	0.012	-0.077***	0.010
Student	–0.011*	0.004	–0.001	0.004	-0.057**	0.022	-0.031	0.018
Other	–0.027***	0.003	–0.021***	0.002	-0.209***	0.013	-0.159***	0.010
Non- metro area	0.003	0.004	0.000	0.004	0.016	0.011	0.014	0.011
Separated/div/widowed	–0.010**	0.003	–0.007**	0.003	-0.068***	0.011	-0.069***	0.009
Single	–0.004	0.003	–0.001	0.002	-0.038***	0.011	-0.020*	0.010
LTHC – no limitations	–0.054***	0.002	–0.053***	–0.002	-0.406***	0.009	-0.396***	0.007
LTHC – limits work	–0.013***	0.001	–0.014***	0.001	-0.129***	0.008	-0.139***	0.008
LTHC – can't work	–0.069***	0.005	–0.065***	–0.004	-0.496***	0.020	-0.485***	0.018
Smoker	–0.002	0.001	–0.001	0.001	-0.039***	0.004	-0.041***	0.004
Previous smoker	–0.001	0.002	0.000	0.002	-0.016*	0.007	-0.006	0.007
Non-drinker	–0.007**	0.002	–0.010***	0.002	-0.048***	0.011	-0.065***	0.008
Drinker	0.001	0.002	0.004**	0.001	0.029***	0.008	0.031***	0.006
No Activity	–0.015***	0.002	–0.016***	–0.002	-0.096***	0.009	-0.093	0.008
Activity 3 + times/week	0.012***	0.001	0.011***	0.001	0.078***	0.007	0.073	0.006
Activity everyday	0.024***	0.002	0.026***	0.001	0.174***	0.008	0.171	0.007
Wave 7	–0.001	0.002	–0.002	0.001	0.001	0.009	-0.007	0.008
Wave 8	–0.004**	0.002	–0.003*	0.002	-0.008	0.009	-0.007	0.008
Wave 9	0.001	0.002	–0.002	0.002	0.031***	0.009	0.003	0.008
Wave 10	–0.006***	0.002	–0.008***	0.002	-0.009	0.009	-0.024**	0.008
Wave 11	–0.006***	0.002	–0.007***	0.002	-0.004	0.009	-0.013	0.008
Wave 12	–0.006***	0.002	–0.007***	0.002	0.006	0.009	-0.014	0.008
Wave 13	–0.009***	0.002	–0.007***	0.002	-0.004	0.009	-0.006	0.008
Wave 14	–0.013***	0.002	–0.011***	0.002	-0.023*	0.009	-0.023**	0.008
Wave 15	–0.014***	0.002	–0.012***	0.002	-0.025**	0.009	-0.029***	0.008
_cons	0.781***	0.005	0.776***	0.004	1.399***	0.018	1.352***	0.015
R^2	0.063		0.063		0.321		0.321	
LL	71528.50		78321.07		–		–	
AIC	–142969		–156554.1		–		–	
BIC	–142577		–156157.4		–		–	
QIC	–		–		130606.7		130693.2	

Due to the GEE not being estimated using a quasi-likelihood method, the R^2 was manually estimated in Stata. Furthermore, there are no information criteria available in which to compare models. A quasi-AIC (QIC) has been proposed to use after GEE models (Pan, 2001), and a Stata command installed that estimated the QIC using a GEE population-averaged model.

3.6.2 Analysis2: BMI change groups

The results from the panel data show the change in QoL following changes in BMI category with the base case identified as a person remaining in a normal weight category over a one-year period (controlling for all sociodemographic variables). Overall, moving from being obese to severely obese was associated with decreased QoL, as was remaining in a severely obese state. All other movements were not associated with any change in QoL, except for a slight increase in QoL for males who remained overweight. The estimated reduction in QoL for males who remained severely obese was –0.002. For females this reduction was estimated to be –0.003. For those individuals who transitioned from severely obese to obese, the resulting reduction in QoL was not significant.

The results from the panel data show the change in QoL following changes in BMI category with the base case identified as remaining in a normal weight category from year 1 to year 2 (controlling for all sociodemographic variables). The resulting changes in QoL for males can be seen in Table 3.14 and for females in Table 3.15. In both males and females, movements from obese to severely obese decreased QoL, as did remaining in a severely obese state. For males, all other movements had no resulting change in QoL, except for a slight increase in QoL for those who remained overweight. For females, becoming obese or severely obese or was also associated with lower QoL. No positive associations of weight loss and QoL were observed.

Table 3.14 QoL changes by BMI category - males

<table>
<tr><th rowspan="2" colspan="2"></th><th colspan="5">Previous wave</th></tr>
<tr><th>Underweight</th><th>Normal weight</th><th>Overweight</th><th>Obese</th><th>Severely obese</th></tr>
<tr><th rowspan="5">Current wave</th><th>Underweight</th><td>–0.007
(-0.030,0.016)</td><td>–0.004
(-0.018,0.009)</td><td rowspan="2">–0.0001
(-0.004,0.005)</td><td rowspan="2">–0.015
(-0.035,0.004)</td><td rowspan="3">0.003
(-0.019,0.024)</td></tr>
<tr><th>Normal weight</th><td rowspan="4">0.004
(-0.009,0.017)</td><td>–</td></tr>
<tr><th>Overweight</th><td>0.004
(-0.0005,0.008)</td><td>0.006**
(0.002,0.011)</td><td>0.0003
(-0.006,0.007)</td></tr>
<tr><th>Obese</th><td rowspan="2">0.025
(0.006,0.045)</td><td rowspan="2">–0.00005
(-0,006,0.006)</td><td>-0.0006
(-0.008,0.006</td><td>–0.003
(-0019,0.024)</td></tr>
<tr><th>Severely obese</th><td>–0.012*
(-0.023,-0.002)</td><td>–0.012*
(-0.023,-0.002)</td></tr>
</table>

Statistically significant at p<0.05, p<0.01** and p<0.001****

Table 3.15 QoL changes by BMI category – females

<table>
<tr><th></th><th></th><th colspan="5">Previous wave</th></tr>
<tr><th></th><th></th><th>Underweight</th><th>Normal weight</th><th>Overweight</th><th>Obese</th><th>Severely obese</th></tr>
<tr><td rowspan="5">Current wave</td><td>Underweight</td><td>–0.013*
(-0.024,-0.002)</td><td>–0.012*
(-0.019,-0.002)</td><td rowspan="2">0.002
(-0.002,0.006)</td><td rowspan="2">–0.004
(-0.019,0.010)</td><td rowspan="3">0.012
(-0.006,0.030)</td></tr>
<tr><td>Normal weight</td><td rowspan="4">–0.008*
(-0.016,-0.0004)</td><td>–</td></tr>
<tr><td>Overweight</td><td>–0.003
(-0.007,0.0006)</td><td>0.001
(-0.003, 0.006)</td><td>0.004
(-0.002,0.011)</td></tr>
<tr><td>Obese</td><td rowspan="2">–0.022**
(-0.037,-0.008)</td><td rowspan="2">–0.010***
(-0.017,-0.004)</td><td>–0.002
(-0.008,0.004)</td><td>–0.001
(-0.010,0.008)</td></tr>
<tr><td>Severely obese</td><td>–0.013**
(-0.021,-0.005)</td><td>–0.010**
(-0.019,-0.001)</td></tr>
</table>

Statistically significant at p<0.05, p<0.01** and p<0.001****

The tables above summarise the changes in QoL for each of the BMI categories relative to the base case of remaining in the normal BMI category. To specify QoL over all BMI movements, post-estimation commands were run in Stata after the full FE and GEE models to estimate the mean QoL for each BMI category movement. Table 3.16 summaries the annual mean QoL for all movements between BMI categories, or remaining in a particular weight category.

Table 3.16 QoL for BMI category movements

Yearly change groups	QoL FE	se	QoL GEE	se
Underweight no change (1)	0.752	0.005	0.753	0.014
Normal weight no change (2)	0.763	0.001	0.767	0.004
Overweight no change (3)	0.766*	0.001	0.764*	0.004
Obese no change (4)	0.760***	0.002	0.753***	0.005
Severely obese no change (5)	0.749***	0.003	0.738	0.008
Underweight to normal weight/overweight/obese/severely obese (6)	0.759	0.003	0.760	0.012
Normal weight to underweight (7)	0.752**	0.004	0.755	0.013
Normal weight to overweight (8)	0.762	0.001	0.763	0.005
Normal weight to obese/severely obese (9)	0.752	0.005	0.747	0.019
Overweight to obese/severely obese (10)	0.763**	0.001	0.764	0.006
Overweight to normal weight/underweight (11)	0.756	0.002	0.750*	0.006
Obese to normal weight/underweight (12)	0.758	0.006	0.756	0.022
Obese to overweight (13)	0.764	0.002	0.758	0.007
Obese to severely obese (14)	0.750***	0.003	0.740**	0.009
Severely obese to underweight, normal weight, overweight (15)	0.768	0.006	0.758	0.023
Severely obese to obese (16)	0.758	0.003	0.750	0.010

±These groups were significantly different than the other change groups All analyses were controlled for age, education, income, marital status, metropolitan status, employment status, long-term health conditions, smoking status, drinking status and physical activity levels.

Sensitivity analysis

A sensitivity analysis was conducted to explore whether changes in BMI (by weight categories) over the 10 waves of data would result in similar effects on QoL. A subset of respondents was created in which QoL and weight data for waves 6 and 15 were available (N=6,762). Nine change groups were constructed to represent any changes between only normal weight/overweight and obese. In the first model, the dependent variable was the QoL (SF-6D score) and a glm model was run, controlling for all socioeconomic demographics as described in Model 4. In the second model, the dependent variable was the change in QoL over the 9 waves for each respondent and an OLS model was run, as the change in QoL was normally distributed. The results of the full models are presented in Appendix 9. Figure 3.7 displays the coefficients from the two models. Overall, individuals who went from normal weight/overweight to obesity or those who remained obese had reduced QoL. In all models, those who were obese in wave 9 and then lost weight to be classified as normal weight or overweight did not have significant changes in QoL. In the second model, using the change in QoL, respondents who changed from obese to overweight had an increase in QoL; however, the result was only weakly statistically significant. These results further indicate that not all reductions in weight produce a gain in QoL, even after controlling for all other explanatory variables.

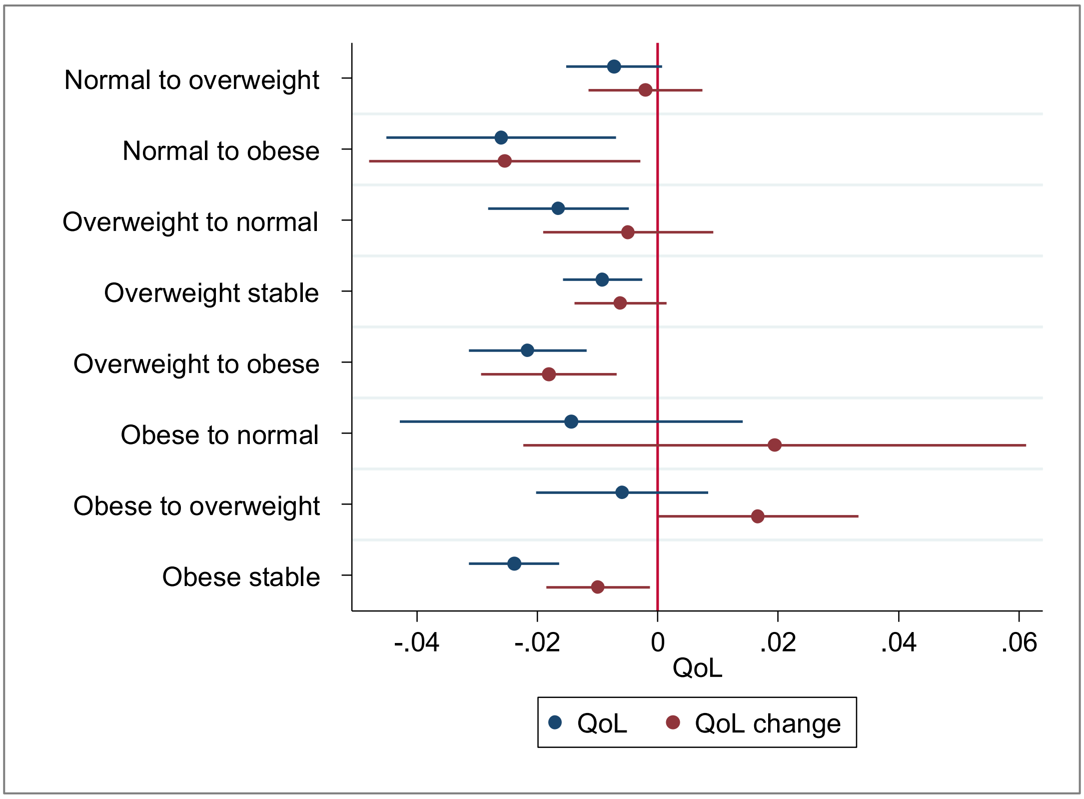


Figure 3.7 QoL by weight changes over 10 waves

Note: all change groups compared to respondents who remained normal weight

3.6.3 Analysis 3: Weight change groups

The analysis was extended to estimate the effects of weight change (in absolute terms) based on kilos lost or gained. The results from the weight change groups demonstrated significant reductions in QoL associated with heavy weight gainers weight gainers and those who lost weight compared to individuals who remained a stable weight. Individuals with the lowest estimated QoL were those who had gained greater than 10% of their body weight. Figure 3.8 illustrates the QoL differences by percentage of body weight change using the unadjusted model.

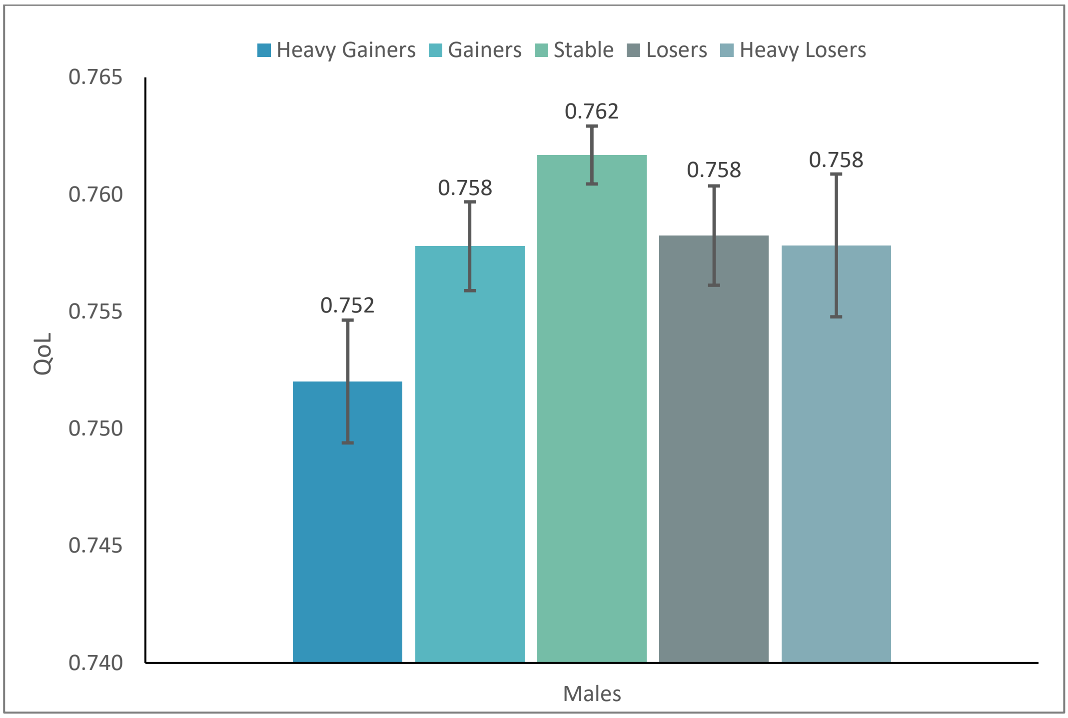


Figure 3.8 QoL by percentage weight gain/ weight loss

Separate analyses were conducted for each weight change group, resulting in significant reductions in QoL associated with increases in BMI for heavy weight gainers, weight gainers, (adjusted for all socio-economic characteristics). Individuals who lost weight also had significant reductions in QoL compared to those who remained a stable weight; however, having a long-term health condition was highly significant, indicating that this had a greater impact on QoL than a change in weight

The full model controlling for all covariates demonstrated that those individuals with heavy weight gain or weight gain relative to those whose weight remained stable, had poorer QoL. Interestingly, there were no significant changes in QoL for females who lost weight, whereas there were significant reductions in QoL for males who had weight loss greater than 10% of their body mass. Similarly, there were greater reductions in QoL for females who had gained weight compared to males. The full models can be found in Appendix 10. Figure 3.9 presents the estimated marginal effects for each weight change group by gender.

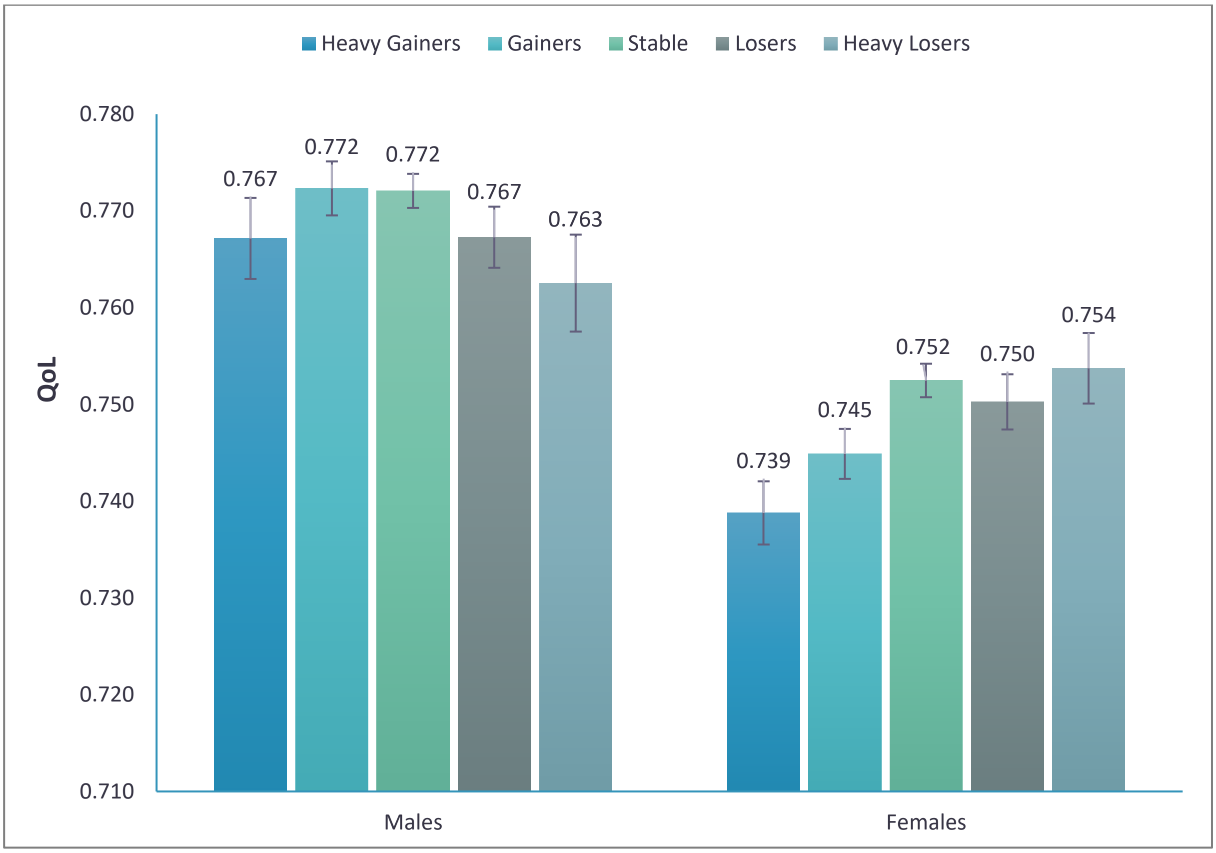


Figure 3.9 QoL by Percentage Weight Change and gender (adjusted model)

Additional analyses were conducted using the interaction between gaining/losing weight and what BMI category an individual is in (using a fixed-effects model). The results indicate that, for females, gaining weight or being obese or severely obese are associated with worse QoL (Table 3.17). For males, being severely obese and losing weight were associated with worse QoL. Conversely, being overweight was associated with higher QoL (a result similarly observed in other studies).

Table 3.17 Weight gain and weight loss by BMI category

	Males	se	Females	se
Underweight	–0.002	0.007	–0.009*	0.004
Overweight	0.004*	0.002	–0.002	0.002
Obese	0.0004	0.003	–0.008**	0.003
Severely obese	–0.012**	0.004	–0.016***	0.004
Gainer	0.003	0.002	–0.006***	0.002
Loser	–0.005*	0.002	–0.002	0.002
Underweight*weight gain	–0.01	0.019	0.003	0.010
Underweight*weight loss	0.001	0.010	0.000	0.006
Overweight*weight gain	–0.003	0.003	0.000	0.003
Overweight*weight loss	0.001	0.003	0.004	0.003
Obese*weight gain	–0.003	0.003	–0.004	0.003
Obese*weight loss	0.001	0.004	0.005	0.003
Severely obese*weight gain	–0.005	0.005	–0.002	0.003
Severely obese*weight loss	0.007	0.007	0.006	0.005
Age 25–34	0.002	0.004	0.008	0.004
Age 35–44	0.003	0.003	0.002	0.003
Age 45–54	–0.007**	0.003	–0.007**	0.002
Age 55–64	–0.012***	0.004	–0.010**	0.003
Age 65–74	–0.017***	0.004	–0.010*	0.004
Age 75+	–0.035***	0.006	–0.027***	0.006
Year 12/certificate/diploma	0.003	0.004	0.002	0.004
Year 11 and below	0.009	0.007	0.000	0.006
OECD income 1	0.000	0.002	–0.001	0.002
OECD income 2	0.000	0.002	–0.002	0.002
OECD income 3	0.002	0.001	–0.003*	0.001
OECD income 5	0.002	0.001	0.000	0.002
Self-employed	–0.005*	0.002	–0.002	0.003
Unemployed	–0.008*	0.003	0.002	0.003
Unpaid housework	–0.017**	0.006	–0.010***	0.002
Retired	–0.011***	0.003	–0.013***	0.002
Student	–0.005	0.005	–0.002	0.004
Other	–0.026***	0.003	–0.021***	0.003
Non- metro area	0.009*	0.004	–0.002	0.004
Separated/divorced/widowed	–0.013***	0.004	–0.009*	0.003
Single	0.001	0.003	–0.001	0.003
LTHC – no limitations	–0.053***	0.002	–0.052***	0.002
LTHC – limits work	–0.013***	0.002	–0.015***	0.002
LTHC – can’t work	–0.069***	0.005	–0.065***	0.005
Smoker	–0.002	0.001	0.000	0.001
Previous smoker	–0.003	0.002	0.001	0.002
Non-drinker	0.006*	0.003	0.011***	0.002
Drinker	0.007*	0.003	0.014***	0.002
No Activity	0.015***	0.002	0.017***	0.002
Activity 3 + times/week	0.028***	0.002	0.028***	0.002
Activity everyday	0.040***	0.002	0.043***	0.002
_cons	0.762***	0.006	0.743***	0.005
R^2	0.058		0.062	
Log-likelihood	57383		63230	
AIC	114675		126370	
BIC	114285		125975	

3.6.4 Analysis 4: PCS and MCS summary scores

The models that were run using MCS and PCS as the dependent variable and BMI groups as the independent variables demonstrated a stronger association between QoL and BMI for the physical health score compared to the mental health score. Those who were obese or severely obese had significant reductions only in the physical aspects of QoL, whereas those who were overweight had increases in the mental aspects of QoL (Table 3.18).

Table 3.18 Physical and Mental QoL and BMI categories

	Physical		Mental	
	Males	**Females**	**Males**	**Females**
Underweight	–0.353	–0.048	–1.577**	–1.302***
Normal Weight	–	–	–	–
Overweight	–0.041	–0.619***	0.421**	0.459***
Obese	–0.428*	–1.384***	0.284	0.100
Severely obese	–1.205***	–2.578***	–0.090	–0.110

Note: All models controlled for sociodemographic variables and time effects

To further evaluate the association between BMI and the different aspects of QoL, BMI changes across 9 waves were analysed by specifying individuals who transitioned to higher or lower weight groups compared to the base case of remaining normal weight. Data to the left of the 0 (no change) line in Figure 3.10 represent decrements in QoL and data to the right represent improvements in QoL. The results demonstrated that remaining obese, transitioning from overweight/normal weight to obese, or remaining overweight had a significant negative effect on physical QoL. None of the changes in BMI had a significant effect on the mental aspect of QoL. This result coincides with the literature, which has also reported that the association between BMI and health-related QoL appears to affect only the physical aspects of QoL.

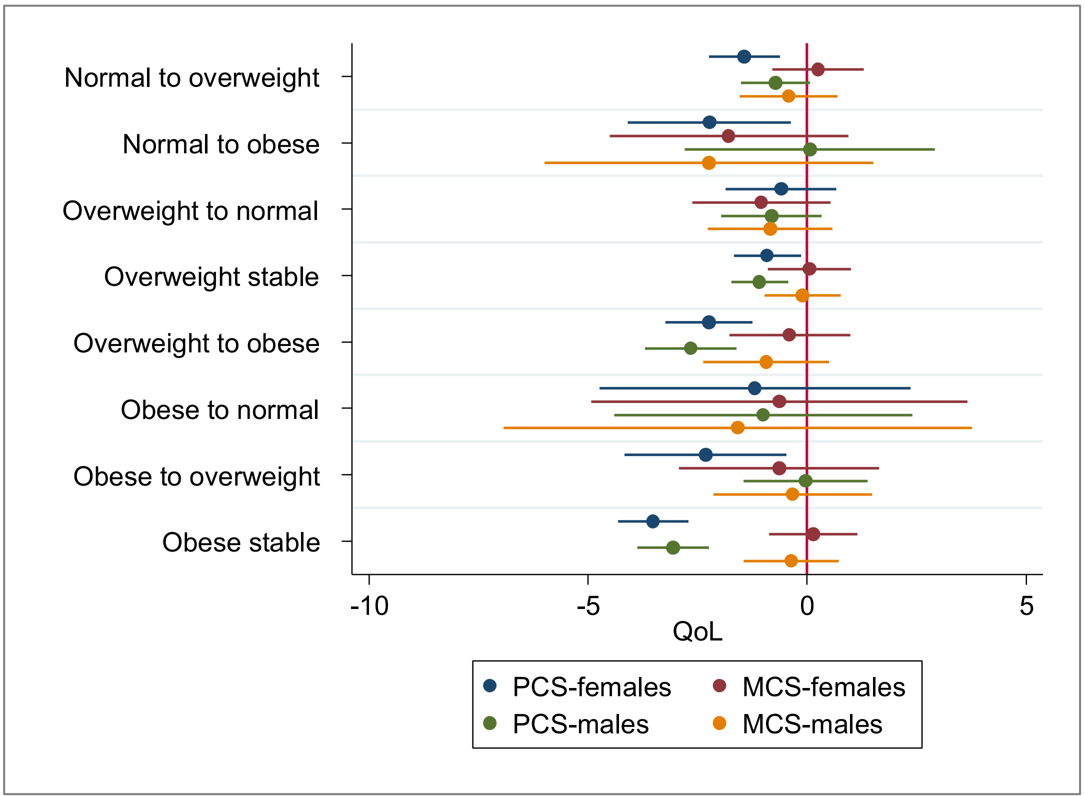


Figure 3.10 PCS and MCS impact from QoL changes (9 waves)

The estimated coefficients for the severely obese were –0.008 for males and –0.022 for females compared to normal weight. Based on a study by Walters and Brazier (2005), these changes in QoL would be considered clinically important. That study estimated that the minimally important difference (MID) in utility ranged from 0.011 to 0.097 for the SF-6D. The MID is defined as "the smallest effect size that would lead them to recommend a therapy to their patients" (van Walraven et al., 1999). In terms of QoL, the MID would represent the smallest difference in terms of improvements in QoL that would change an individual's treatment (Gandhi et al., 2012). Some researchers however, have expressed concern over the utilisation of a MID with respect to cost-effectiveness research. Whitehurst & Bryan (2013) reason that concept of MID in a clinical setting relates to a single clinical outcome at the patient level, making it too restricted for application in economic evaluation, which considers the differences in both costs and outcomes that are being evaluated.

3.7 Discussion

The results demonstrated that, compared to normal weight, all other BMI categories are associated with a lower QoL. The magnitude of the effect is lessened however, when controlling for sociodemographic and economic characteristics. This analysis demonstrated that having a long-term health condition, and more specifically one that limits the ability to work, accounts for the majority of loss in QoL. Increasing age also significantly impacts QoL negatively, which the model also predicted.

3.7.1 Comparison with previous research

The result that being obese is associated with impaired health-related QoL is consistent with previous studies (Daviglus et al., 2003; Doll et al., 2000; Ford et al., 2001; Jia & Lubetkin, 2010; Larsson et al., 2002; Soltoft et al., 2009; Stafford et al., 1998; Sturm & Wells, 2001). Moreover, the results are consistent with the two previous studies using HILDA that also showed that changes in BMI are negatively associated with QoL (Kortt & Dollery, 2011; Renzaho et al., 2010). Unlike Renzaho et al., 2010, the results in this chapter show a significant association between BMI and both the physical and mental aspects of QoL. This finding also differed from the cross-sectional studies that showed weight gain was associated with significant declines in physical QoL (Ford et al., 2001; Hassan et al., 2003; Huang et al., 2006; Jia & Lubetkin, 2010; Larsson et al., 2002; Sach et al., 2007; Yancy et al., 2002). The longitudinal analysis, which demonstrated that movements from a higher BMI category did not have a significant impact on QoL, differs from the results of studies of interventions that consistently show improvements in QoL associated with weight loss (Fontaine & Barofsky, 2001; Kolotkin et al., 2001; Picot et al., 2009).

The longitudinal analysis demonstrated that movements from a higher BMI category did not have a significant impact on QoL, which differs from the results from studies of interventions that consistently show improvements from weight loss (Fontaine & Barofsky 2001; Kolotkin 2001; Picot 2009).

3.7.2 Gender differences

There were significant differences between men and women in terms of weight change and resulting changes in QoL. Body image may have a greater impact on women, which may explain a lower QoL in overweight women compared to overweight men. Increased stress has been suggested as a reason women have increased fat distribution (based on the waist-to-hip ratio[37]) (Epel et al., 2000).

[37] The wait to hip ratio is also an obesity screening tool that estimates fat distribution. Cutoffs of >0.9 for males and >0.8 for females are indicative of increased risk of comorbidities. http://meteor.aihw.gov.au/content/index.phtml/itemId/270207

Populating models that have time component, with people moving in and out of different BMI categories, is an approach that reflects changes in BMI and the corresponding changes in QoL. This study aimed to quantify these changes for more precise estimates of utility for use in economic evaluation. The results suggest that any reductions in QoL were due to remaining underweight, or remaining obese or severely obese for both males and females. A gain in QoL was witnessed for males who remained overweight over a one-year timeframe. All other movements compared to remaining normal weight were not significant. The result of increased QoL in overweight men compared to normal weight is of interest, as it is counterintuitive. One explanation could be BMI incorrectly categorising men with muscle mass as overweight or obese without the associated health risks of these categories. This result has also been demonstrated in other studies; for example, de Hollander found that only persistently overweight men did not show lower QoL scores than persistently healthy weight persons (de Hollander et al., 2013). The results may lend support for treatment to prevent people becoming severely obese, as this weight category had significant QoL decrements, both for those moving into this state and those remaining in this state.

3.7.3 Strengths and limitations

The use of the HILDA dataset, which offers 15 waves of data and is representative of the general population of Australia, is a major strength in this analysis. The use of the SF-36 in the dataset is also a strength, given that it is a well-established, widely used tool that has been extensively validated in previous research. The large sample size included in the study (N= ~10,000 per wave) is also an advantage over smaller studies that have previously been based on trials or small cohorts with higher attrition rates. Using a study based on the general population excludes the selection bias that exists in studies alongside a trial comparing QoL and weight change.

An interesting feature of this study was the use of BMI change categories, unlike previous longitudinal studies that used groups categorised by weight loss, stable weight, small gain, moderate gain and large gain. The advantage of the BMI change categories is that they refer directly to the states one would see in a Markov model of obesity. There are some limitations, however, in using BMI, as it does not account for the distribution of body fat (intra-abdominal versus overall adiposity). It has been suggested that the risk of comorbidities associated with obesity are greater in those who carry their weight around the abdomen versus the hips, as the fat accumulates around essential organs (Stern & Kazaks, 2015). However, a study published in the *Lancet*, which followed 220,000 individuals over a decade, concluded that BMI, waist-to-hip ratio and waist circumference all had similar impacts on the risk of heart attack or stroke (The Emerging Risk Factors Collaboration, 2011).

One issue with the use of BMI in research is that it is commonly derived from self-reported height and weight, which can be misreported by respondents. It has been demonstrated that, overall, individuals tend to overstate their height and understate their weight, resulting in underestimated BMI (Gorber et al., 2007; Krul et al., 2011). A study by the ABS found that in the 2007–08 National Health Survey, the discrepancy between self-reported and measured BMI understated the proportion of individuals in the overweight and obese categories. Persons misreporting more frequently were those with poorer health, of older age and female (ABS, 2012). Overweight and obese individuals tend to underreport to a greater degree, with one in seven obese individuals misclassified as being non-obese (Burkhauser & Cawley, 2008; Cawley et al., 2015). The implication for this research is that there may have been an over-representation of normal weight individuals who were in fact overweight and obese. Whether this would have impacted the overall significance between BMI and QoL is uncertain. However, recognising the issues and limitations of the BMI measurement, the ease with which BMI can be collected and calculated makes it well-suited for large population epidemiological studies. The major advantage of using BMI is the comparability of results with other research.

The HILDA survey currently has ten waves of weight and height data, which provides nine data points for each respondent about their weight change, limiting any long-term analyses. Also, an individual could start at severely obese in year 1 then lose weight in year 2 to a normal range then regain the weight to be obese. These multiple patterns have not been quantified and only changes from one year to another are analysed. Furthermore, the effects of overweight and obesity on QoL may manifest later in life and the ten waves of data may not capture this. The HILDA survey currently uses an UK algorithm to convert the SF-36 scores to SF-6D utility values. It is possible that preferences for particular health states may differ between the UK and Australian populations. In addition, the Australian algorithm was derived using DCE methods opposed to the UK algorithm derived using standard gamble which may underestimate changes in QoL. The pattern, however would remain similar overtime and the use of the same algorithm over each wave provides the ability to study changes over time.

A further limitation when looking at the change in weight overtime is the inability to distinguish between changes in weight that were intentional versus unintentional. While controlling for long-term health conditions can mediate some of this effect, there still is potential for bias in the results.

3.7.4 Implications

The finding that the biggest impact on QoL over time appeared to be in those who gain weight may indicate that more emphasis should be placed on the prevention of obesity. This coincides with the previous literature demonstrating that QoL decreases with weight gain but does not improve with weight loss (Laxy et al., 2014).

The findings from this chapter also support the growing literature that the relationship between QoL and obesity differs in respect of mental and physical health. In particular, the meta-analysis by Ul-Haq et al. (2013) demonstrated that the physical health scores were significantly lower for all BMI categories compared to normal weight. This differs from the findings for mental health, in which only participants with class III obesity ($\geq$40 kg/m^2) had significantly lower mental health scores, and participants considered overweight had increased QoL. This result indicates the need for further research to disentangle how mental aspects related to weight persist after weight loss. In this study, the biggest impact in QoL over time appeared to be in those who gain weight, which may indicate that more emphasis should be placed on the prevention of obesity (Laxy et al., 2014). This coincides with the previous literature demonstrating QoL impairment with weight gain but no improvement with weight loss. Moreover, the targeting of public health interventions may be more appropriate to specific groups, such as those who remain obese or severely obese over time.

3.8 Conclusion

Quantifying the link between BMI and QoL is appealing, since BMI is a common primary outcome measure in many clinical trials of obesity interventions. However, by using the results from cross-sectional studies, economic models to assess the cost-effectiveness of these interventions may be overestimating the QoL gain following a reduction in BMI. Overall, the results from this chapter demonstrated that there are reductions in QoL from weight gain and remaining obese or severely obese; however, these results are not reversed when losing weight. The results showed no increase in QoL for those who were obese or severely obese and moved into a lower BMI category. Furthermore, it appears that the effects of increased body mass impact the physical rather than the mental aspects of QoL. The following chapter will explore this further.

4 EXPLORING ENDOGENEITY WITH OBESITY AND QOL

As the previous chapter demonstrated, weight loss does not necessarily result in gains in QoL. A potential explanation for this may be underlying conditions affecting QoL beyond high body mass, which may persist even after a reduction in weight. For example, increases in BMI may be due to life events causing depression; thus, subsequent reductions in BMI will not necessarily increase QoL unless the underlying depression is addressed (Dixon et al., 2004).

The relationship between obesity and depression is well-established; however, it is uncertain in which direction the causality runs. There appears to be a 'feedback' loop whereby both are continually affecting the other. People with mental health issues are twice as likely to be obese as those without such issues (McElroy, 2009). To confound the issue, many medications prescribed for mental illness also increase the propensity to gain weight. Obesity is therefore both a predictor and an outcome of depression, with the current evidence demonstrating a reciprocal link exists between depression and obesity. (Luppino et al., 2010). Longitudinal studies of obesity and QoL, such as Cameron et al. (2012), have found a bi-directional association exists between health related QoL and obesity. Given that reduced QoL is both a consequence and a predictor of obesity, further insight is needed into the causes of reduced QoL preceding obesity.

Most obesity-related interventions target weight loss through increased activity and dietary changes; however, there may be other factors simultaneously affecting the likelihood of becoming obese that deserve more attention than obesity alone. The role of depression and its link with obesity is important, as both conditions have a direct impact on QoL. This chapter aims to explore the impact of QoL and depression on obesity and the causal link between these two health states.

4.1 Obesity and stressful life events

The link between depression and obesity has been explored quite extensively. Stunkard et al. (2003) found that obesity was associated with major depression in women, while an inverse relationship was found in men. Another cross-sectional study found that obese people had significantly lower SF-36 scores for most age-matched physical and emotional component measures (Anandacoomarasamy et al., 2009). Similarly, obese men and women are more likely than normal weight individuals to report stressful life events (Barry & Petry, 2008). An explanation for this association is that stress may contribute to weight gain through psychological stress response or negative effects on eating and exercise habits.

The link between stressful life events and depression is widely accepted. Kessler (1997) was instrumental in highlighting the link between stressful life events and the onset of depressive episodes, supporting initial research on psychosocial factors that contribute to depression (Brown & Harris, 1978; Brown et al., 1973). A recent systematic review of studies conducted between 1980 and 2002 also found evidence of stressors on depression (Tennant, 2002). Large twin studies have reported that the variation in depression between twins can be explained more by life stressors than genetic factors, past history of depression or neuroticism (Kendler et al., 1999). Deb et al. (2011), using only one stressful life event (job loss), found that individuals who responded to job loss by increasing their tendency to engage in unhealthy behaviours were already engaged in these types of behaviours before the event. Iversen et al. (2012) used panel data from Copenhagen to show that the experience of a major life event was associated with future weight gain and obesity, especially for women. The vehicle by which the stressful life event affected weight gain was not explored, but the study showed that both men and women with vital exhaustion[38] experienced more weight gain. This link between stressful life events and depression may be a useful instrument in disentangling the loop of causality between depression and obesity.

A stressful life event cannot directly cause weight gain; it is the response to such events that may bring about psychological or behavioural changes, which may then affect body weight. These changes in body weight may further affect an individual's mental health. Models built to predict propensity to being obese may neglect to take into account this loop of causality. Using a two-stage analysis that simultaneously estimates the effect of depression and obesity arising from stressful life events as an instrumental variable may offer more insights into understanding how individuals become obese. Many of the results from studies have been inconclusive or contradictory in regards to the relationship between BMI and QoL (Ul-Haq et al., 2013).

[38] Vital exhaustion is defined as a state of exhaustion that is characterised by 'unusual fatigue and lack of energy, increasing irritability and feelings of demoralisation, typically attributed to prolonged psychological stress' (Tselebis et al., 2011). It also appears to be caused more by depressed mood than by loss of vigour and excess fatigue.

4.2 Endogeneity

In economics, it is a concern when other causes of the outcome are correlated with the explanatory variables. In a linear model $y = x\beta + u$, we are interested how y is related to x, where the error term u captures the unexplained variation in y. However, when other causes of y are correlated with x, endogeneity can occur and the estimate of β will be biased and inconsistent. Endogeneity can arise in the following situations (Auld & Grootendorst, 2011):

- there are errors when measuring x
- y causes x (reverse causality)
- there are variables that affect both y and x that are not included in the model (unobserved heterogeneity).

If any of these issues are present, it is difficult to make accurate inferences about the effect of obesity (and weight loss) on QoL, as the assumptions underpinning OLS are violated. Factors such as personality, cognitive ability and family background may affect both QoL and obesity at the same time. One approach to mitigate endogeneity is to use covariate adjustment, which involves including additional variables in the model to control for common causes of both x and y. However, such solutions may remedy the omitted variable bias without solving the problem completely (Auld & Grootendorst, 2011). Furthermore, the model will lose efficiency as more variables are added.

The literature does, however, report a reciprocal link that supports a reverse causality between obesity and depression. A meta-analysis of longitudinal studies provides further evidence for the bi-directional association between obesity and depression (Luppino et al., 2010). Similarly, the evidence demonstrates a bi-directional association between obesity and QoL (Cameron et al., 2012). An instrumental variable (IV) regression approach is a common method used in econometrics to address reverse causality. OLS regressions will collapse due to the explanatory variable (*QoL*) being correlated with the regression error term (u) when regressing on the dependent variable (*obesity).* Even if additional control variables are added into the model, the results would still be biased due to reverse causality. By adding an additional variable (z), called an instrument, that is correlated with the explanatory variable (*QoL*) but uncorrelated with ε, the issue of reverse causality can be constrained. Figure 4.1 illustrates how the instrument z is not correlated with error term (u) but is correlated with the explanatory variable (x).

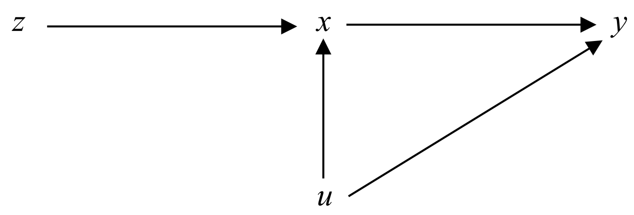


Figure 4.1 Instrumental variable approach for reverse causality

4.2.1 Instrumental variables

In economics, IVs are useful to explore causal relationships in a non-experimental setting. Research in obesity is mainly conducted using observational data. It would be very difficult (and unethical) to design an experiment to change an individual's body mass to observe the effect on their QoL (or vice versa). Moreover, it is not possible to randomise individuals by individual characteristics (Auld & Grootendorst, 2011). In an IV analysis, the following conditions need to be met (Jia & Skaperdas, 2012):

1) The instrument must be correlated with the endogenous explanatory variables
2) The instrument cannot be correlated with the error term in the explanatory equation.

An instrument is considered suitable if it affects the dependent variable but has no independent effect on the dependent variable. Consequently, the causality between the dependent and independent variable can be assessed. IV analyses involve a two-step process that 'relies on exploiting exogenous variation in the treatment variable that is independent of the outcome' (Jones, 2007). However, if the instrument used to estimate the model is weak, the IV estimates may not be an improvement over OLS estimates. The general model for IV estimation is as follows:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{u} \tag{4-1}$$

In equation (4-1), y is the dependent variable we are interested in estimating, Z is a matrix of endogenous variables, X is a matrix of included instruments and u is the error term (uncorrelated with Z). Stata has built-in commands for performing analyses with IV, the 'ivreg' command, plus a command to check the model for weak instruments, 'ivreg2'.

In the previous chapter, the effect of obesity on QoL was estimated using a linear framework. A test for endogeneity can be conducted in Stata, using a two-stage model, as recommend by

Wooldridge (2016). For example, in the first model BMI is the dependent variable with all other explanatory variables. The predicted residuals of that model are then used in a second model where QoL is the dependent variable along with BMI and the other explanatory variables. The statistic for the residuals in the model tests the null that BMI is exogenous. If the null is rejected, an instrumental variable is required. This new test for endogeneity in Stata was released in Stata 14 'estat endogenous'.

4.3 Stressful life events model

This chapter will explore the hypothesis that the main consequence of stressful life events on an individual's QoL is the impact on their mental health, as measured through depression and anxiety (Schwarzer, 2002). An IV analysis using stressful life events as the instrument will be specified. Figure 4.2 illustrates the model that will be used to conceptualize the impacts of stressful life events, QoL/depression and obesity and the numerous pathways of causation.

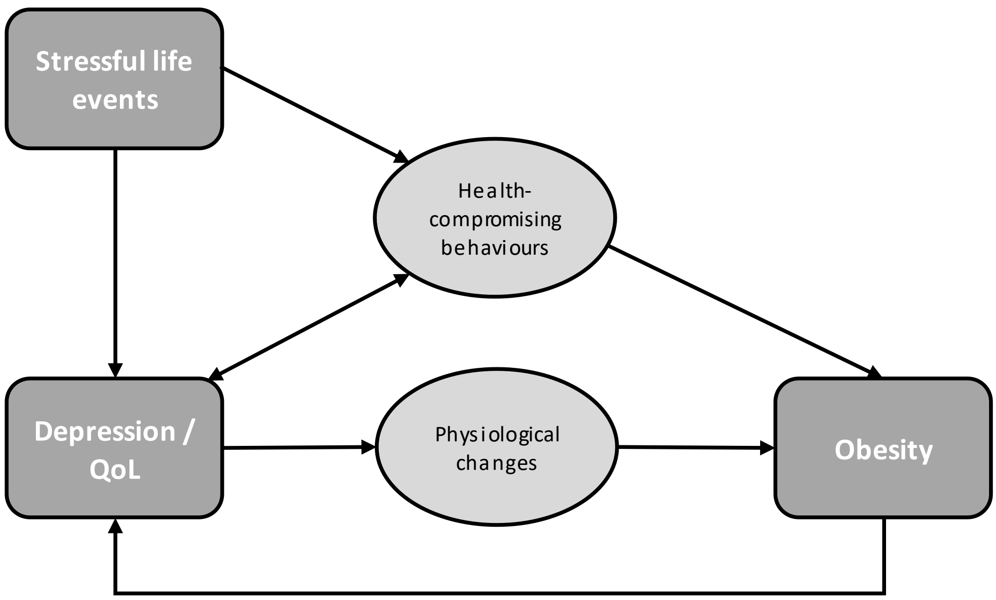


Figure 4.2 Schematic Diagram of Model

The overarching assumption in the model is that stressful life events do not impact on obesity directly. Stressful life events have a direct impact on QoL and any resulting depression can cause physiological changes, such as hormone and immune changes that increase an individual's likelihood of becoming obese. Another avenue by which an individual's weight may be affected by stressful life events is through health-compromising behaviours such as increased caloric intake, increased alcohol consumption and low levels of activity. The main focus of this chapter is on the pathway between stressful life events and obesity via depression and change in QoL; this addresses the research question as to whether there are factors other than changes in weight that could be influencing QoL in people who are obese. The results will clarify whether an endogeneity issue does exist and whether the above model is a valid representation of the dynamic between stressful life events, depression and weight changes.

4.4 Methods

4.4.1 Data

Data for this analysis were obtained from the HILDA survey. A previous description of the HILDA survey was presented in Chapter 3, Section 3.2.1. The sociodemographic variables used in this analysis were the same as those in the previous chapter. A description of each variable can be found in section 3.2. The new HILDA variables used in this chapter are discussed below.

4.4.2 Depression variables

Multiple variables are included in the HILDA survey that can be used to identify people diagnosed with depression or anxiety. These include health questions about serious medical conditions, long-term health conditions, as well as the SF-36 mental health dimension (MH) and the mental health summary score (MCS).

Long-term health condition – depression/anxiety

A health module was included in waves 7 and 9 and asked respondents to provide information on serious medical conditions. The question labelled 'lshedep' asked respondents '*Have you ever been told by a doctor or nurse that you have any of the long-term health conditions listed below*[39]*? Please only include those conditions that have lasted or are likely to last for six months or more'*. Those respondents who chose the long-term health condition *'Depression/Anxiety'* were used to construct a variable to denote someone as with depression and/or anxiety.

Serious illness/medical condition – depression/anxiety

Additionally, in waves 9 and 13, the variable labelled 'hedep' was included to derive information on serious illnesses. The respondents were asked '*Have you been told by a doctor*

[39] The list of health conditions/serious illnesses were: arthritis, asthma, any type of cancer, chronic bronchitis or emphysema, depression or anxiety, Type 1 diabetes (childhood onset), Type 2 diabetes, high blood pressure/hypertension, heart/coronary disease, other circulatory condition (eg stroke or hardening of arteries), other mental illness

or a nurse that you have any of these conditions? Please only include current conditions that have lasted or are likely to last for 6 months or more'.[40] Those respondents who chose '*Depression or anxiety*' were dummy coded in the dataset to indicate a respondent diagnosed with depression and/or anxiety. These data can be cross-referenced with the SF-36 summary scores to validate the use of the mental health (MH) or the composite mental health summary score (MCS), which are collected in every wave.

SF-36 Mental Health Summary Scores

Depression scores can be derived from the mental health (MH) dimension of the SF-36 (as this dimension alone can be indicative of emotional problems), as well as the composite mental health summary score (MCS). The MCS is derived from four of the eight dimensions of the SF-36; vitality, social functioning, role-emotional and mental health (Table 4.1). Section 3.2.2 explains how the measures were calculated using Australian population norms.

Table 4.1 SF-36 and summary scores

SF-36 dimensions	Health and well-being focus	Summary scores
Physical functioning **(PF)**	Extent to which a person is limited by their health in performing a range of physical activities (such as bathing and dressing) on a typical day	Physical health summary score **(PCS)**
Role physical **(RP)**	Effects of physical health on an individual's performance on work or other daily activities	
Bodily pain **(BP)**	Extent of pain impacting normal activities	
General health **(GH)**	Combination of self-assessed health and perceptions of health relative to others	
Vitality **(VT)**	Indication of energy levels and levels of fatigue	Mental health summary score **(MCS)**
Social functioning **(SF)**	Impact of health or emotional problems on quality or quantity of social interactions or activities	
Role emotional **(RE)**	Effect of emotion problems on work performance or other daily activities	
Mental health **(MH)**	Indication of time a person experiences feelings of nervousness, anxiety, depression and happiness	

A MH score of 52 or below and a MCS score of 42 or below are considered the cut-offs for depression (Matcham et al. 2016). Both the MH and MCS have been validated as screening tools for depression (Table 4.2).

[40] The list of serious medical conditions included: arthritis or osteoporosis, asthma, any type of cancer, depression or anxiety, Type 1 diabetes, Type 2 diabetes, high blood pressure or hypertension, heart disease, any other circulatory condition (stroke, hardening of arteries), other mental illness, chronic bronchitis or emphysema.

Table 4.2 Depression cut-off scores

	MH Score	MCS Score
Probable depression	=< 48	
Cut off value	52	=< 42
Possible depression	52-60	
Unlikely depression	60+	

Source: Silveira, 2005.

A study validating these cut-offs found the suggested cut-off points of 52 and 42 for the MH and MCS scores compared favourably to their results regardless of age or culture (Silveira, 2005). Both the MH and MCS were predictors of depression; however, the study found that the MH scale performed better than the MCS. Moreover, estimating the number of respondents who were diagnosed as depressed (using long-term health and serious medical conditions questions from HILDA) and comparing this proportion to both the MH and MCS cut-off values, the MH score captured a greater number of individuals diagnosed as depressed. Therefore, the MH score cut-off was used in the econometric analysis to denote individuals as depressed.

4.4.3 Stressful life events

Starting in wave 2, the HILDA survey has captured the occurrence of major life events in the dataset each year. In the self-completion questionnaire, the following question was asked of respondents: *'We now would like you to think about major events that have happened in your life over the past 12 months. For each statement cross either the YES box or the NO box to indicate whether each event happened during the past 12 months. If you answer "YES", then also cross one box to indicate how long ago the event happened or started'.* The following life events were included in the question:

- got married
- separated from spouse or long-term partner
- pregnancy/pregnancy of partner
- serious personal injury or illness to self
- serious illness to a close relative/family member
- death of spouse or child
- death of other close relative/family member (e.g., parent or sibling)
- death of a close friend
- victim of physical violence (e.g., assault)

- victim of a property crime (e.g., theft, housebreaking)
- retired from the workforce
- fired or made redundant by an employer
- major worsening in financial situation (e.g., bankruptcy).

The questions further asked respondents whether the life event occurred 0–3 months ago, 4–6 months ago, 7–9 months ago or 10–12 months ago. A dummy variable was constructed for each major life event. An additional variable was constructed that combined all life events (minus pregnancy and marriage) to represent ‘experienced a life event’ or ‘did not experience a life event’. Furthermore, a dummy variable was created to represent a life event experienced in the preceding year to the wave being analysed.

4.5 Empirical Framework Data Analysis

4.5.1 Summary statistics

Summary statistics were calculated for the sample of respondents in terms of weight and depression status. Table 4.3 summarises the variables and statistical analyses used in the summary statistics.

Table 4.3 Summary statistics

Summary Table	Statistical Method	Table reference
Depression diagnosis by BMI weight group	Proportions	Table 4.5
MH and MCS cut-offs by BMI weight group/wave	Proportions	Table 4.6
Summary statistics by demographics	Proportions	Table 4.7
BMI by demographics	Means	
SF-6D by demographics	Means	
Depressed status by demographics	Proportions	
Depression/obesity stressful by stressful life events	Proportions	Table 4.8

4.5.2 Preliminary analyses

A preliminary analysis was conducted to explore the association between the stressful life events, weight status (both BMI and obesity) and QoL (SF-6D, MCS, PCS) as well as the propensity to be depressed. A fixed effects regression with the resulting significance of the coefficients was estimated to demonstrate any significant associations.

Secondly, a preliminary econometric analysis (unadjusted for any covariates) was conducted to test whether there were any indications of endogeneity between QoL and obesity. First, a simple probit model was conducted that pooled all the observations for each respondent for each wave.

Second, a fixed effects regression model was run to cluster observations by each respondent. The final models estimated the possible endogeneity using a biprobit model, Model 3 using only using stressful life events and Model 4 using both stressful life events and previous stressful life events.

4.5.3 Econometric analysis

The final results were conducted using models that controlled for all the covariates and a combination of econometric analyses given the specification of continuous regressors or dichotomous regressors. All analyses were conducted using Stata 15.

The econometric analysis initially used bivariate probit models, which specify both regressors as binary variables. This model was extended to take advantage of instrumental variable commands in Stata using an ivprobit model. The bivariate probit and instrumental bivariate probit regressions are useful to evaluate the relationship between obesity and depression, but only for one wave, and do not incorporate the panel nature of the data. Moreover, both dependent variables in the specification need to be binary, which limits the applicability.

Current Stata commands have limitations in that many models cannot be estimated, such as an unbounded continuous variable on an instrumented binary variable; a continuous variable on a left-censored variable; or an instrumental ordered probit. A conditional mixed-process (cmp)[41] framework allows for different dependent variables to be estimated (for example, continuous and probit) or any combination of linear, binary or categorical variables. The standard errors can be specified and complex survey designs using 'svy' can be estimated. Although the command is not specifically written for panel data, the observations can be clustered around the respondent id. The following econometric models were estimated (Table 4.4):

Table 4.4 Econometric models using life events as an instrument

	Statistical method	Outcome	Treatment	Instrument
Model 1	biprobit	obese (1/0)	MH depressed (1/0)	all life events, lag of life events
Model 2	cmp	obese (1/0)	MH depressed (1/0)	all life events, lag of life events
Model 3	cmp	BMI	MH depressed (1/0)	all life events, lag of life events
Model 4	ivprobit	obese (1/0)	QoL (SF-6D)	all life events, lag of life events
Model 5	cmp	obese (1/0)	QoL (SF-6D)	all life events, lag of life events
Model 6	cmp	BMI	QoL (SF-6D)	all life events, lag of life events

[41] The conditional mixed process is a user written command by David Roodman and can be installed using 'ssc install cmp' and 'ssc install ghkw'.

Explanatory variables included in all models were gender, age, marital status, metropolitan area, presence of a long-term health condition, educational attainment, OECD-equivalised income quintiles, metropolitan area, smoking status, alcohol consumption and activity levels. These are all defined in Section 3.2.4.

The models used a 'life shock' dummy variable that combined all stressful life events (minus pregnancy and marriage) into one variable to represent 'experienced a stressful life event' or 'did not experience a stressful life event' and estimated the effect of having experienced this stressful life event in the preceding year on being depressed in the current wave. The model was further extended to incorporate lags in the life event instrumental variable to analyse the timing of a stressful life event and the effect on depression. A variable was constructed that included any of the stressful life events experienced in the previous wave (which would denote approximately 24 months previously). Stressful life events are used as an instrument in the model, as it is hypothesised that life events will affect obesity indirectly through depression.

Analysis 1: Two-stage depression models

Models 1 and 2 were used to estimate the simultaneous equations of depression and obesity using stressful life events as an instrumental variable. The models were conducted using a two-stage method as follows:

$$\begin{aligned} \boldsymbol{D_i^*} &= \boldsymbol{x_i}' \ \boldsymbol{\beta_2} + \boldsymbol{L_i \delta_{t-1}} + \boldsymbol{\mu_i} \quad t=(0,1) \\ \boldsymbol{W_i^*} &= \boldsymbol{x_i}' \ \boldsymbol{\beta_1} + \boldsymbol{D_i \gamma} + \boldsymbol{\varepsilon_i} \end{aligned} \tag{4-2}$$

In the models, D is a binary outcome representing depression, x is a vector of socioeconomic and demographic explanatory variables, L are the stressful life events experienced and W is the propensity to be obese or BMI as a continuous variable.

Analysis 2: Two-stage QoL models

The final extension was to incorporate QoL into the model using the SF-6D utility score and evaluate any stressful life events on overall QoL (not only the mental aspects of QoL). Stata includes an instrumental variable probit (ivprobit) command that was used to explore endogeneity and compare results.

$$\begin{aligned} \boldsymbol{Q_i^*} &= \boldsymbol{x_i}' \ \boldsymbol{\beta_2} + \boldsymbol{L_i \delta_{t-1}} + \boldsymbol{\mu_{i,}} \\ \boldsymbol{W_i^*} &= \boldsymbol{x_i}' \ \boldsymbol{\beta_1} + \boldsymbol{Q_i \gamma} + \boldsymbol{\varepsilon_i} \qquad t=(0,1) \end{aligned} \tag{4-3}$$

In the models, Q is a binary outcome for QoL, x is a vector of socioeconomic and demographic explanatory variables, L are the stressful life events experienced and W is the propensity to be obese or BMI as a continuous variable.

It was assumed that the analyses would not suffer significantly from omitted variable bias as the majority of common causes were controlled for in the model. The model included variables such as age and long-term health conditions that have a direct impact on weight and QoL. Other variables such as income, education and marital status were also included in the model. Activity levels were included as research has demonstrated that increased activity levels are associated with better mental health outcomes and QoL, as well impacting on body mass.

4.5.4 Sensitivity analysis

The first sensitivity analysis was conducted using a five-year lag on stressful life events to denote that the respondent experienced a life event at some point in time previous to the current wave. An additional sensitivity analysis was conducted only using the stressful life events that were not associated with the probability of being obese. The life events included in the sensitivity analysis were personal injury, injury of a family member, victim of violence and worsening of finances. A further sensitivity analysis was conducted identifying individuals as engaging in poor health-related behaviours.

4.6 Results

4.6.1 Summary statistics

Both variables included in the HILDA data asking respondents about a diagnosis of depression or a long-term condition (depression or anxiety) were used to explore the prevalence of depression in obesity (Table 4.5). Overall, a larger proportion of females were considered depressed. Being underweight is associated with the highest prevalence of depression for both males and females, and respondents who are considered normal weight have the lowest prevalence of depression (except for wave 9 using the diagnosed depression variable).

Table 4.5 Depression diagnosis by BMI weight group

	Serious Illness Diagnosed depressed		Long-term condition Depression or Anxiety	
	Wave 9	**Wave 13**	**Wave 7**	**Wave 9**
	N=5,589	**N=7,679**	**N=10,149**	**N=10,245**
Males				
Underweight	48.3%	40.9%	26.1%	26.3%
Normal weight	19.5%	19.8%	9.9%	10.9%
Overweight	18.4%	24.3%	12.6%	13.2%
Obese	19.9%	20.4%	16.2%	16.3%
Severely obese	21.6%	21.2%	18.2%	16.9%
Total Males	*19.9%*	*21.6%*	*12.7%*	*13.3%*
Females				
Underweight	39.1%	39.7%	20.8%	20.9%
Normal weight	24.9%	26.5%	17.7%	19.4%
Overweight	30.9%	32.9%	18.8%	19.8%
Obese	21.2%	30.9%	20.8%	22.9%
Severely obese	25.3%	30.8%	31.2%	25.8%
Total females	*26.7%*	*30.4%*	*19.5%*	*20.7%*

Figures 4.3 and 4.4 display the prevalence of depression by the specific weight categories for each of the waves for which the data were captured. These graphs demonstrate that a higher proportion of severely obese and underweight individuals have been diagnosed with depression or anxiety. However, the variable pertaining to long-term health conditions appears to result in a broader distribution between the weight categories.

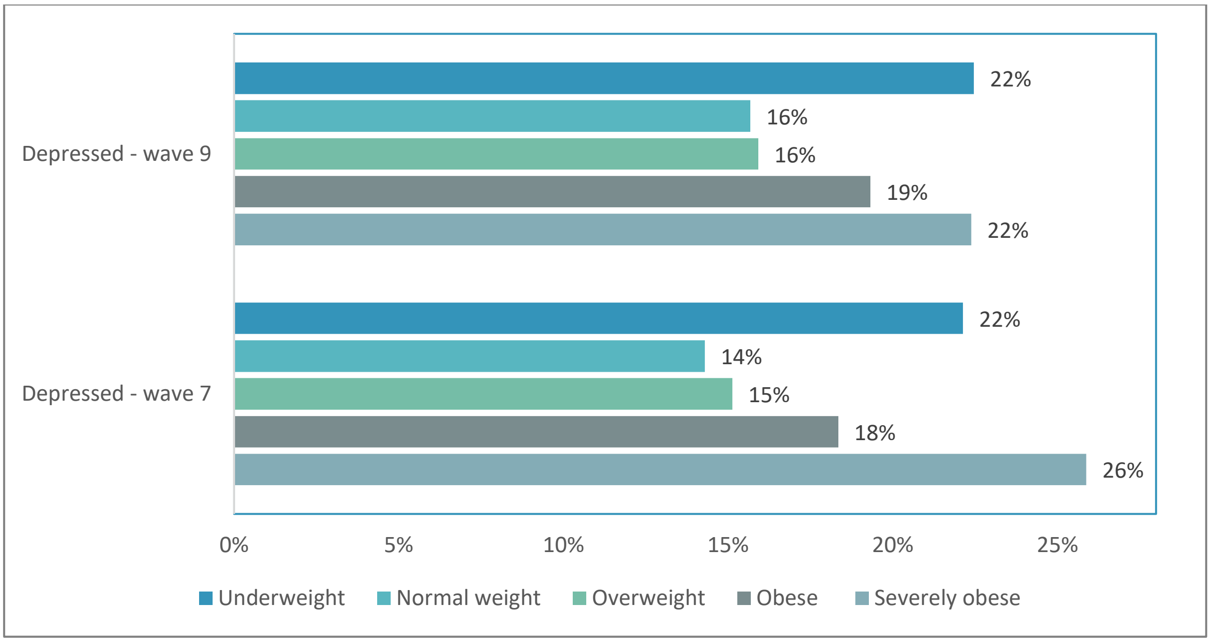


Figure 4.3 Long-term health condition (depression) by weight category

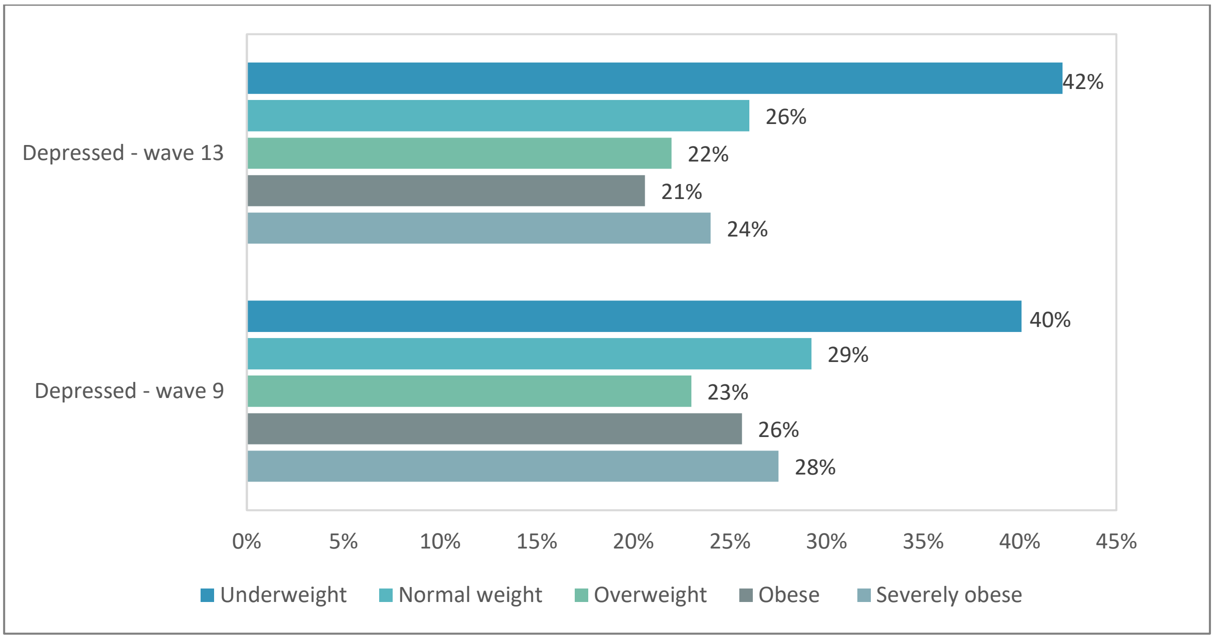


Figure 4.4 Serious illness (depression) by weight category

The cut-offs from the mental health aspect of the SF-36 were also used to classify respondents as depressed. The proportion of individuals in the weight categories based on both the MH cut-off of =<52 and the MCS cut-off of =<42 were calculated across all waves (Table 4.6). The MCS summary score appears to predict a higher proportion of depressed individuals for both males and females across all weight categories. Overweight males are less likely to be depressed based on these data. Overall, the results demonstrate that the prevalence of depression is higher for those individuals who are obese compared to those who are normal weight or overweight.

Table 4.6 MH and MCS cut-offs for depression by BMI weight group

	Wave 6	Wave 7	Wave 8	Wave 9	Wave 10	Wave 11	Wave 12	Wave 13	Wave 14	Wave 15
MH dimension score =< 52										
Males										
Underweight	18.0%	26.5%	17.4%	19.6%	14.8%	15.9%	15.7%	36.2%	13.6%	15.4%
Normal weight	10.4%	11.6%	9.8%	10.5%	10.5%	11.4%	12.6%	11.2%	12.1%	12.5%
Overweight	13.0%	12.1%	13.1%	11.9%	12.5%	10.9%	9.7%	12.3%	13.4%	10.7%
Obese	12.5%	12.0%	14.7%	16.4%	10.7%	13.5%	15.6%	13.0%	15.3%	16.6%
Severely obese	13.7%	13.9%	11.7%	13.7%	12.0%	14.8%	15.5%	13.1%	20.4%	18.7%
Females										
Underweight	23.4%	19.1%	19.7%	15.1%	20.6%	17.0%	21.3%	21.2%	14.9%	19.9%
Normal weight	16.1%	13.7%	12.7%	14.4%	14.9%	12.5%	14.4%	13.6%	13.1%	14.7%
Overweight	15.6%	13.7%	13.5%	13.9%	14.7%	11.6%	12.6%	13.3%	13.8%	14.0%
Obese	12.3%	14.6%	14.6%	15.4%	15.7%	15.6%	14.9%	17.0%	16.6%	18.5%
Severely obese	22.7%	18.8%	18.7%	20.6%	18.9%	21.2%	20.8%	17.6%	21.5%	21.9%
MCS summary score =<42										
Males										
Underweight	43.1%	27.2%	24.7%	40.0%	26.6%	20.1%	27.3%	26.6%	20.8%	43.1%
Normal weight	17.2%	17.9%	16.4%	16.5%	16.8%	18.7%	17.9%	16.5%	18.8%	20.0%
Overweight	19.1%	19.0%	20.8%	16.3%	19.9%	19.3%	15.8%	18.6%	18.2%	17.1%
Obese	16.4%	19.5%	19.2%	21.0%	21.2%	18.4%	20.5%	20.3%	24.8%	23.2%
Severely obese	26.2%	23.1%	22.4%	23.1%	20.1%	28.5%	23.4%	19.5%	28.5%	26.8%
Females										
Underweight	31.8%	27.7%	35.8%	31.9%	28.4%	30.3%	27.3%	23.4%	23.5%	26.7%
Normal weight	21.4%	20.4%	21.8%	21.5%	20.8%	22.4%	22.3%	20.5%	21.0%	23.7%
Overweight	22.7%	22.0%	22.1%	23.0%	22.6%	20.2%	19.4%	20.3%	22.0%	23.3%
Obese	23.9%	24.3%	23.3%	22.0%	22.4%	25.0%	24.4%	24.5%	26.7%	28.2%
Severely obese	28.2%	27.0%	27.6%	25.9%	27.5%	30.5%	29.7%	26.3%	32.4%	30.8%

The summary statistics in Table 4.7 show the breakdown of various socioeconomic and demographic variables on the full dataset, with the mean BMI, SF-6D score and the percentage considered depressed (based on the mental health dimension).

Table 4.7 Summary statistics by depression and obesity status

	Respondents	%	Mean BMI	Mean SF-6D	Depressed -%
Male	7,898	47.2%	27.35	0.765	13.0%
Female	8,849	52.8%	26.89	0.744	16.0%
Age					
15–24	2,278	13.6%	24.9	0.773	19.3%
25–34	3,266	19.5%	26.4	0.779	15.2%
35–44	2,676	16.0%	27.5	0.767	16.0%
45–54	2,851	17.0%	27.9	0.757	14.0%
55–64	2,492	14.9%	28.1	0.740	13.6%
65–74	1,884	11.3%	28.0	0.731	10.6%
75+	1,300	7.8%	26.3	0.684	12.0%
Marital Status					
Married/living together	10,305	61.5%	27.3	0.763	12.1%
Separated/divorced/widow	3,027	18.1%	27.8	0.713	17.4%
Single	4,413	20.4%	26.0	0.759	20.1%
Remoteness					
Metropolitan area	14,631	87.4%	27.0	0.755	14.7%^
Non-metropolitan area	2,115	12.6%	27.9	0.744	14.6%^
Employment status					
Employee	9,090	54.3%	26.8	0.782	12.1%
Self-employed	1,574	9.4%	26.9	0.777	9.7%
Unemployed	716	4.3%	27.1	0.728	28.6%
Unpaid housework	1,107	6.6%	27.7	0.727	20.0%
Retired	3,001	17.9%	27.4	0.708	12.5%
Student	299	1.8%	24.9	0.752	22.5%
Other	960	5.7%	29.1	0.636	34.6%
Education					
Degree or higher	4,415	26.4%	26.0	0.777	11.0%
Year 12, certificate, diploma	8,244	49.2%	27.3	0.757	14.7%
Year 11 or below	4,088	24.4%	28.2	0.719	18.6%
Long-term health condition (LTHC)					
No LTHC	11,786	70.5%	26.5	0.791	10.2%
LTHC – limits work	3,217	19.2%	28.9	0.636	28.0%
LTCH – no limitations	1,456	8.7%	27.8	0.737	17.2%
LTCH – can’t work	263	1.6%	29.1	0.563	37.4%
OECD equivalised income					
OECD quintile 1 (lowest)	3,354	20.0%	27.6	0.694	22.0%
OECD quintile 2	3,307	19.8%	27.4	0.740	16.4%
OECD quintile 3	3,304	19.7%	27.2	0.762	13.9%
OECD quintile 4	3,366	20.1%	26.9	0.778	12.3%
OECD quintile 5 (highest)	3,416	20.4%	26.4	0.788	9.2%
Smoking					
Non-smoker	12,019	82.3%	27.1^	0.760	12.5%
Smoker	2,587	17.7%	27.1^	0.724	24.2%
Drinking					
Non-drinker	6,057	41.4%	27.6	0.732	11.9%
Drinker	8,560	58.6%	26.7	0.769	17.6%
Activity					
No activity	1,775	12.1%	29.0	0.663	27.3%
2	2,536	17.3%	28.2	0.732	18.1%
3	5,659	38.6%	27.0	0.761	13.2%
4	4,692	32.0%	26.0	0.790	9.7%

^ *p-value was not significant, indicating that the groups were not statistically significantly different from each other. All other groups differed by mean BMI, mean SF-6D and proportion depressed.*

In terms of educational attainment, a higher proportion of respondents with a Year 11 education level or below are depressed, with a larger mean BMI and lower QoL. Depression is much higher (22.0%) for those in the lowest OECD income bracket that for those in the highest OECD income bracket (9.2%). In terms of employment status, the mean BMI is relatively similar; however, those respondents who are employed, self-employed or retired have much lower levels of depression. A large proportion (34.6%) of those in the 'other' category were depressed; this category refers to individuals not in the labour force but for whom the reason is unknown.

The percentage of depressed individuals is much lower for those with higher activity levels, a result that would be expected given the aetiology of both conditions. In terms of alcohol consumption, a higher proportion of drinkers and ex-drinkers are considered depressed. The drinking category however, does not capture the quantity of drinking to ascertain different levels of alcohol intake. A higher percentage of smokers are also depressed. A higher proportion of respondents with a long-term condition had depression. Given the cross-sectional nature of the summary statistics, it is not possible to infer whether the long-term health conditions affect the propensity to be obese or depressed or if the reverse holds – that is, if obesity or depression increases the propensity to have a long-term health condition

The summary statistics for the stressful life events provide support to the hypothesis that the experience of stressful life events impacts on mental health rather than having a direct effect on obesity. A higher proportion of depressed respondents overall had experienced a life event, with the largest differences between the depressed and non-depressed population being experiencing a separation from spouse, personal injury, an injury of a family member, victim of violence or worsening of finances (Table 4.8).

Table 4.8 Depression and obesity prevalence by stressful life events

	Depression status			Obese status		
	Not Depressed	Depressed	p-value	Not obese	Obese	p-value
Married	2.1%	1.7%	0.288	2.2%	1.7%	0.092
Separated	2.8%	7.1%	<0.000	3.7%	3.1%	0.097
Pregnant	5.8%	4.9%	0.110	5.7%	5.2%	0.264
Injury to self	8.0%	17.8%	<0.000	8.5%	12.8%	<0.000
Injury to family	13.9%	20.8%	<0.000	14.3%	17.0%	<0.000
Death spouse/child	0.6%	1.4%	<0.000	0.7%	0.8%	0.498
Death family member	11.4%	15.7%	<0.000	11.1%	14.3%	<0.000
Death close friend	10.3%	13.1%	<0.000	10.0%	13.6%	<0.000
Victim of violence	0.7%	4.0%	<0.000	1.3%	1.1%	0.439
Victim of crime	3.0%	5.0%	<0.000	3.2%	3.4%	0.521
Retired	2.8%	2.9%	0.731	2.7%	3.4%	0.041
Fired/made redundant	3.4%	5.9%	<0.000	3.7%	3.6%	0.703
Worsening of finances	1.9%	8.8%	<0.000	2.8%	3.3%	0.104
All life events	42.7%	57.6%	<0.000	43.3%	50.6%	<0.000

p-value denotes whether the percentage of respondents who experienced a stressful life event differed in terms of those who are depressed/not depressed or those who are obese or not obese.

The percentage of respondents experiencing a stressful life event was estimated for all waves, with injury to a family member the most commonly experienced stressful life event, followed by injury to self and death or a family member or close friend. The prevalence of these stressful life events in the HILDA population was consistent across waves Figure 4.5.

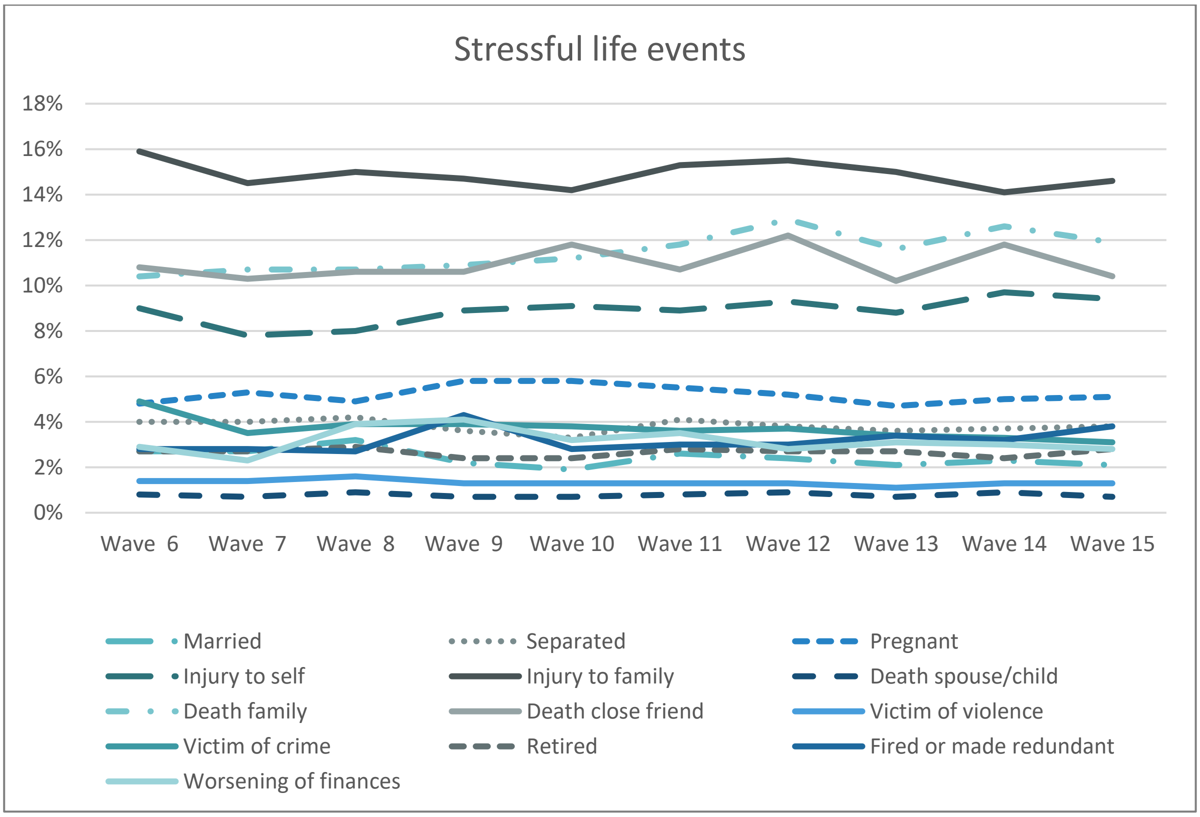


Figure 4.5 Prevalence of stressful life events by wave

4.6.2 Preliminary results

Exploration of stressful life event variables

The panel nature of the data was exploited to determine the relationship between stressful life events and weight measurements and QoL variables. A fixed effects regression was conducted separately for each stressful life-event to control for any unobservable factors, and all regressions controlled for sociodemographic covariates. The significance of each stressful life event for BMI, the odds of being obese, QoL, PCS, MCS and odds of being diagnosed with depression is presented in Table 4.9.

The results demonstrate that all stressful life events, except for marriage and pregnancy, increased the odds of being depressed (last column), and these results were all significant. A similar result was obtained using the MCS summary score. There were fewer associations between obesity and the physical aspects of QoL, with the largest impacts from injury to self and being retired. In terms of overall QoL, all stressful life events were associated with decreased QoL, except for marriage. There was a lower level of association between weight and stressful life events. The odds of being obese significantly increased when there was an injury to a family member, death of a family member, death of a close friend or a worsening in finances. Results for BMI as a continuous measurement demonstrated increases in BMI from being fired, victim of crime and death of a family member. Using BMI as the dependent variable may not capture the effect of life events consistently, given the effect of life events affecting both extremes (underweight and obesity).

Table 4.9 Stressful life events by weight, QoL and depression status

	BMI	Obese	QoL	PCS	MCS	Dep_MH
Got married	0.007	1.075	0.001	–0.044	0.550***	0.769***
Separated	–0.352***	0.679***	–0.021***	1.203***	–3.492***	2.608***
Pregnant	0.620***	1.576***	–0.005***	–0.860***	0.381***	0.813***
Injury to self	–0.065**	1.041	–0.067***	–5.535***	–2.884***	2.419***
Injury to family	–0.009	1.119**	–0.012***	–0.130*	–1.135***	1.441***
Death spouse/child	–0.136	0.951	–0.039***	0.216	–3.996***	2.656***
Death family	0.057**	1.182***	–0.009***	–0.073	–0.793***	1.336***
Death close friend	–0.003	1.14**	–0.010***	–0.634***	–0.441***	1.186***
Victim of violence	–0.389***	0.797*	–0.032***	0.321*	–4.338***	3.232***
Victim of crime	–0.073*	0.919	–0.009***	0.043	–0.914***	1.318***
Retired	0.044	1.005	–0.019***	–1.748***	–0.657***	1.276***
Fired/made redundant	0.094*	1.079	–0.008***	0.488***	–1.359***	1.794***
Worsening of finances	–0.082*	1.207*	–0.040***	–0.249*	–4.730***	4.305***

*Significance levels: * p<0.05; ** p<0.01; *** p<0.001, All models controlled for age, gender, education, income, marital status, metropolitan area, employment status, long-term conditions, smoking, drinking and physical activity levels.*

In all the models, pregnancy was excluded from the analysis. Interestingly, this life event was positively related to the MSC score (indicating better mental health) but negatively correlated with the PCS (indicating worse physical health). Moreover, pregnancy directly impacts a woman's weight and therefore would contradict the model. The only other stressful life event to have a positive effect on mental health or overall QoL was getting married. The life shocks included in the model must be such that the effect on obesity is mediated through effects on QoL; stressful life shocks that could have a direct impact on weight changes would not be considered good instruments. Therefore, the stressful life events of injury to self were excluded, as this could directly impact the ability to move and exercise, thus directly affecting weight.

Obesity and depression (unadjusted)

The preliminary analyses explored the use of a two-stage model by using models that build upon one another. In Model 1 (Table 4.10), a biprobit model that pooled all the waves of data was used; the results indicate that there is an increased likelihood of obesity in depressed individuals. In Model 2, the panel nature of the data was used to explore this relationship further while controlling for any unobservable factors within individuals. Similarly, the resulting coefficient indicated that there is a greater likelihood of depressed individuals being obese. Model 3 used a bivariate approach and the results are closer to expectations. The χ^2 test indicates that the null hypothesis can be rejected; $\rho=0$, indicating that depression and obesity are not independent. In Model 4, the life event variable used further indicates that a current life event is a good instrument in the reduced form equation and has more impact on depression than a life event in the preceding year. A test for joint significance between the life event variables used as instruments was conducted and, given the resulting χ^2 test, the null hypothesis that they are jointly linear was rejected.

Table 4.10 Obesity and depression - unadjusted models

	Model 1 probit		Model 2 xtprobit		Model 3 biprobit		Model 4 biprobit with lag	
Obesity: predicted Model								
Depression score ≤ 52	0.193***	(0.012)	0.091**	(0.029)	1.273***	(0.074)	1.354***	(0.072)
_cons	–0.750***	(0.004)	–4.263***	(0.025)	–0.839***	(0.005)	–0.816***	(0.005)
Depression: Reduced Model								
Recent SLE					0.321***	(0.009)	0.272***	(0.011)
SLE in past year							0.172***	(0.010)
_cons					–1.293***	(0.006)	–1.372***	(0.009)
R^2	0.0021							
Rho			0.959		–0.566		–0.605	
χ^2 (p-value)					148.32***		165.15***	
Log-liklihood	–64355		–33848		–106252		–81727	
AIC	128714		67702		212515		163467	

*SLE: Stressful life event; Significance levels: * p<0.05; ** p<0.01; *** p<0.001*

Obesity and QoL (unadjusted)

A two-stage model was also used to explore endogeneity between obesity and QoL (Table 4.11). A biprobit model was used first, which pooled all the waves of data, indicating a negative association between obesity and QoL. In Model 2, the panel nature of the data was used to explore this relationship further while controlling for any unobservable factors within individuals. Models 3 and 4 used an ivprobit and the Wald tests of endogeneity (p-values <0.001) indicated that there is endogeneity within the models.

Table 4.11 Obesity and QoL - unadjusted models

	Model 1 probit		Model 2 xtprobit		Model 3 ivprobit		Model 4 ivprobit with lag	
Obesity: predicted Model								
SF-6D score	–1.530***	(0.033)	–1.681***	(0.097)	–2.841***	(0.160)	–3.285***	(0.564)
_cons	0.427***	(0.025)	–2.404***	(0.078)	1.438***	(0.124)	1.627***	(0.435)
Qol: Reduced Model								
corr (Recent SLE)					0.163	(0.20)	0.203	(0.072)
corr (SLE in past year)							0.120	(0.001)
R^2	0.0174							
Rho			0.947					
χ^2 (p-value)			59000***		63.74***		7.38**	
Log-likelihood	–63,710		–33,343		19138		871	
AIC	125209		66692		–38264		–1728	

*SLE: Stressful life event; Significance levels: * p<0.05; ** p<0.01; *** p<0.001*

Given that results for both the depression and QoL unadjusted models (models 3 and 4) suggest the errors are correlated, it is necessary to account for endogeneity. A further test for endogeneity was conducted using a simple model with BMI, QoL and life shocks using an IV regression. The Durbin and Wu-Hausman tests are used for the null hypothesis that QoL can be treated as exogenous. The test results indicate that this is not the case (p<0.000) and the null is rejected. Therefore, the models need to treat QoL as endogenous. Furthermore, the χ^2 estimate from both the biprobit models indicated that there was significant correlation between the residuals, so a two-stage estimation is the preferred method.

4.6.3 Final results

Given that the preliminary analyses suggest the errors are correlated and that there is a need to account for endogeneity, full models were conducted controlling for socioeconomic and demographic characteristics. The final models were estimated using a variety of econometric analyses. In the first set of analyses, depression was used as the outcome for the life events model; for the second set of analyses, QoL was used as the outcome for stressful life events.

4.6.4 Outcome: Depression (MH score)

The following models use the MH dimension to indicate depression In Model 1, a pooled approach across the waves was estimated using the biprobit command. In Model 2, a cmp model was used to cluster data around respondents. In Model 4, the dependent variable was BMI. Table 4.12 presents the results from the three models.

In all models, a recent stressful life event was a good instrument for predicting depression, even after controlling for other characteristics. Once clustering around id, the overall significance of depression for obesity in Model 2 is increased over the biprobit. The existence of a long-term health condition and increased age is also highly associated with an increased likelihood of obesity. In Model 3, the largest reduction in depression was associated with respondents with long-term health conditions, no physical activity or less than weekly physical activity and unemployed. Respondents aged 55+ had reduced levels of depression compared to the base case age group of (35–44). Once controlling for depression in the full model, having a long-term health condition, lower levels of education and being male were associated with higher BMI.

Table 4.12 Instrumental variable analysis – life shocks on depression

	Model 1		Model 2		Model 3	
	Obese		Obese		BMI	
	biprobit	se	cmp	se	cmp	se
Predicted Model						
Depression score ≤52	0.104	0.086	0.062*	0.027	0.083	0.156
Male	0.036***	0.010	0.038	0.020	1.281***	0.092
Age 18–24	–0.440***	0.022	–0.446***	0.034	–2.770***	0.165
Age 25–34	–0.189***	0.016	–0.189***	0.026	–0.843***	0.127
Age 45–54	0.018	0.015	0.027	0.025	0.248*	0.122
Age 55–64	0.042*	0.017	0.034	0.030	0.685**	0.145
Age 65–74	–0.086***	0.024	–0.0.098**	0.038	–0.036	0.180
Age 75+	–0.552***	0.032	–0.580***	0.049	–2.625***	0.226
Year 12, cert or diploma	0.273***	0.013	0.273***	0.026	0.770***	0.104
Year 11 or below	0.420***	0.015	0.403***	0.030	0.686***	0.134
Sep/divorced/widow	0.027*	0.013	0.016	0.025	–0.129	0.123
Single	–0.032*	0.016	–0.050	0.028	–0.657***	0.139
OECD income 1st decile	–0.039*	0.017	–0.014	0.024	–0.656***	0.126
OECD income 2nd decile	0.013	0.015	0.017	0.019	–0.139	0.100
OECD income 4rd decile	0.015	0.015	0.025	0.030	0.252**	0.091
OECD income 5rd decile	–0.044**	0.015	–0.040	0.019	–0.090	0.102
Rural area	–0.101***	0.014	–0.105***	0.027	–0.336*	0.143
Self-employed	–0.110***	0.017	–0.101***	0.032	–0.405**	0.123
Unemployed	0.062*	0.031	0.063*	0.024	–0.495*	0.198
Unpaid housework	–0.001	0.020	–0.002	0.030	–0.378*	0.181
Retired	–0.063**	0.020	–0.051	0.032	–0.129*	0.149
Student	–0.178***	0.044	–0.167***	0.049	–0.570**	0.213
Other	–0.043	0.025	–0.026	0.031	–0.434*	0.185
LTCondition limits work	0.295***	0.018	0.290***	0.021	1.304***	0.121
LTCondition nolimitations	0.234***	0.017	0.225***	0.020	0.921***	0.111
LTCondition can't work	0.227***	0.048	0.261***	0.051	1.014***	0.333
Smoker	–0.112***	0.013	–0.105***	0.023	–0.893***	0.112
Drinker	–0.187***	0.010	–0.183***	0.018	–0.396***	0.087
None or less than weekly	0.175***	0.018	–0.168***	0.022	0.251	0.138
1–2 times a week	0.143***	0.014	0.149***	0.016	0.548***	0.089
Every day	–0.242***	0.012	–0.236***	0.015	–0.737***	0.066
_cons	–0.675***	0.025	–0.684***	0.042	27.713***	0.212
Depression: Reduced Model						
Recent stressful life event	0.196***	0.012	0.194***	0.012	0.194***	0.012
Stressful life event in last year	0.086***	0.012	0.082***	0.012	0.082***	0.012
Male	–0.030**	0.012	–0.033	0.020	–0.033	0.020
Age 18–24	0.001	0.024	0.001	0.033	0.001	0.033
Age 25–34	0.056**	0.019	–0.059*	0.026	–0.059*	0.026

	Model 1		Model 2		Model 3	
	Obese		Obese		BMI	
	biprobit	**se**	**cmp**	**se**	**cmp**	**se**
Age 45–54	–0.085***	0.019	–0.089***	0.026	–0.089***	0.026
Age 55–64	–0.317***	0.022	–0.325***	0.032	–0.325***	0.032
Age 65–74	–0.587***	0.030	–0.587***	0.043	–0.587***	0.043
Age 75+	–0.810***	0.036	–0.792***	0.052	–0.792***	0.052
Year 12, cert or diploma	0.019	0.015	0.023	0.024	0.023	0.024
Year 11 or below	0.071***	0.018	0.078**	0.029	0.078**	0.029
Sep/divorced/widow	0.162***	0.016	0.167***	0.025	0.167***	0.025
Single	0.200***	0.017	0.201**	0.027	0.201**	0.027
OECD income 1st decile	0.089***	0.020	0.093***	0.026	0.093***	0.026
OECD income 2nd decile	0.001	0.019	0.004	0.021	0.004	0.021
OECD income 4rd decile	–0.045*	0.018	0.048*	0.024	0.048*	0.024
OECD income 5rd decile	–0.096***	0.019	–0.097***	0.025	–0.097***	0.025
Rural area	0.053**	0.018	0.059*	0.029	0.059*	0.029
Self-employed	–0.050*	0.022	–0.056	0.030	–0.056	0.030
Unemployed	0.331***	0.031	0.339***	0.035	0.339***	0.035
Unpaid housework	0.123***	0.024	0.126***	0.030	0.126***	0.030
Retired	0.117***	0.027	0.121***	0.037	0.121***	0.037
Student	0.198***	0.045	0.189***	0.052	0.189***	0.052
Other	0.315***	0.025	0.305***	0.032	0.305***	0.032
LTCondition limits work	0.639***	0.016	0.632***	0.021	0.632***	0.021
LTCondition nolimitations	0.322***	0.020	0.321***	0.024	0.321***	0.024
LTCondition can't work	0.746***	0.047	0.764***	0.057	0.764***	0.057
Smoker	0.156***	0.015	0.156***	0.022	0.156***	0.022
Drinker	–0.122***	0.012	–0.118***	0.018	–0.118***	0.018
No activity/< weekly	0.368***	0.018	–0.179***	0.024	–0.179***	0.024
Activity 1–2 times a week	0.198***	0.016	–0.372***	0.023	–0.372***	0.023
Activity every day	–0.187***	0.015	–0.556***	0.025	–0.556***	0.025
_cons	–1.507***	0.030	–1.137***	0.046	–1.137***	0.046
N		88,298		120,297		122,137
Rho		–0.051		0.043		–0.025
Log-likelihood		–74,741		–90,246		459199
AIC		149,614		180,624		918,373
BIC		150,234		181,264		919,024

*Significance levels: * p<0.05; ** p<0.01; *** p<0.001*

4.6.5 Outcome: Quality of life (SF-6D)

The effect of stressful life events on overall QoL was estimated using QoL as a continuous variable. A cmp analysis was conducted using the dichotomous dependent variable of obese or continuous BMI (Table 4.13).

Table 4.13 Instrumental variable analysis – life shocks on QoL

	Model 4 Obese		Model 5 Obese		Model 6 BMI	
	ivprobit	se	cmp	se	cmp	se
Predicted Model						
QoL	–3.342***	0.362	–0.868***	0.088	-2.370***	0.623
Male	0.067***	0.011	0.045*	0.021	1.300***	0.091
Age 18–24	–0.423***	0.022	–0.443***	0.034	-2.756***	0.165
Age 25–34	–0.187***	0.017	–0.188***	0.026	-0.833***	0.127
Age 45–54	–0.014	0.016	0.019	0.025	0.268*	0.122
Age 55–64	0.026	0.017	0.032	0.030	0.675***	0.145
Age 65–74	–0.075**	0.023	–0.095*	0.038	-0.031	0.179
Age 75+	–0.555***	0.029	–0.576***	0.049	-2.560***	0.225
Year 12, cert or diploma	0.278***	0.013	0.277***	0.026	0.782***	0.103
Year 11 or below	0.429***	0.015	0.410***	0.030	0.705***	0.133
Sep/divorced/widow	–0.008	0.014	0.004	0.025	-0.144	0.123
Single	–0.056***	0.016	–0.055*	0.028	-0.671***	0.138
OECD income 1st decile	–0.090***	0.018	–0.029	0.024	-0.682***	0.126
OECD income 2nd decile	–0.001	0.016	0.014	0.019	-0.146	0.100
OECD income 4rd decile	0.021	0.015	0.027	0.019	0.256**	0.091
OECD income 5rd decile	–0.023	0.016	–0.034	0.024	0.104	0.102
Rural area	–0.103***	0.014	–0.105***	0.027	-0.341*	0.142
Self–employed	–0.125***	0.017	–0.110***	0.030	-0.414***	0.123
Unemployed	0.003	0.032	0.054	0.032	-0.503*	0.198
Unpaid housework	–0.042	0.021	–0.014	0.030	-0.398*	0.181
Retired	–0.116***	0.022	–0.071*	0.032	-0.179	0.149
Student	–0.223***	0.049	–0.178***	0.050	-0.541*	0.214
Other	–0.179***	0.029	–0.060	0.031	-0.482**	0.186
LTCondition limits work	–0.118*	0.048	0.189***	0.023	0.989***	0.139
LTCondition no limitations	0.108***	0.022	0.194***	0.021	0.816***	0.114
LTCondition can't work	–0.299***	0.075	0.129*	0.052	0.606	0.345
Smoker	–0.161***	0.015	–0.115***	0.023	-0.942***	0.112
Drinker	–0.163***	0.011	–0.178***	0.018	-0.381***	0.087
None or less than weekly	0.026	0.023	0.132***	0.022	0.172	0.138
1–2 times a week	0.081***	0.016	0.134***	0.016	0.505***	0.090
Every day	–0.171***	0.014	–0.220***	0.015	-0.681***	0.067
_cons	1.999***	0.290	0.009	0.083	27.612***	0.542
QoL: Reduced Model						
Recent stressful life event			–0.023***	0.001	-0.023***	0.001
stressful life event in last year			–0.011***	0.001	-0.011***	0.001
Male			0.010***	0.001	0.010***	0.001
Age 18–24			0.006**	0.002	0.006**	0.002
Age 25–34			0.000	0.002	0.000	0.002
Age 45–54			–0.008***	0.002	-0.008***	0.002
Age 55–64			–0.002	0.002	-0.002	0.002
Age 65–74			0.006*	0.002	0.006*	0.002
Age 75+			–0.002	0.003	-0.002	0.003
Year 12, cert or diploma			0.001	0.001	0.001	0.001
Year 11 or below			0.001	0.002	0.001	0.002
Sep/divorced/widow			–0.010***	0.002	-0.009***	0.002
Single			–0.007***	0.002	-0.007***	0.002

	Model 4 Obese		Model 5 Obese		Model 6 BMI	
	ivprobit	se	cmp	se	cmp	se
OECD income 1st decile			–0.016***	0.002	-0.016***	0.002
OECD income 2nd decile			–0.004***	0.001	-0.004***	0.001
OECD income 4rd decile			0.001	0.001	0.001	0.001
OECD income 5rd decile			0.006***	0.001	0.006***	0.001
Rural area			–0.002	0.002	-0.002	0.002
Self–employed			–0.002	0.002	-0.002	0.002
Unemployed			–0.018***	0.003	-0.017***	0.003
Unpaid housework			–0.013***	0.002	-0.013***	0.002
Retired			–0.012***	0.002	-0.012***	0.002
Student			–0.014***	0.003	-0.012***	0.003
Other			–0.040***	0.003	-0.040***	0.003
LTCondition limits work			–0.123***	0.002	-0.123***	0.002
LTCondition no limitations			–0.037***	0.002	-0.037***	0.002
LTCondition can't work			–0.158***	0.004	-0.159***	0.004
Smoker			–0.015***	0.002	-0.016***	0.002
Drinker			0.010***	0.001	0.009***	0.001
No activity/< weekly			–0.046***	0.002	-0.046***	0.002
Activity 1–2 times a week			–0.020***	0.001	-0.020***	0.001
Activity every day			0.023****	0.001	0.023***	0.001
_cons			0.810***	0.003	0.810***	0.003
N	87,432		119,025		120,667	
rho			0.006		–0.004	
χ2	48.78***					
Log–likelihood			23,969		–340,038	
AIC			–47,804		680,212	
BIC			–47,155		680,872	

*Significance levels: * p<0.05; ** p<0.01; *** p<0.001*

The presence of a current stressful life event appears to predict reduced QoL, indicating that the use of stressful life events is a good instrument in the reduced form equation and has more impact on QoL than a previous stressful life event. A test for joint significance between the life event variables used as instruments was conducted and, given the resulting χ^2 test, the null that they are jointly linear can be rejected. The sign of the QoL variable is as expected, with a decrease in QoL associated with obesity. The largest decrements in QoL were associated with respondents with long-term health conditions, unemployed, separated/divorced or widowed, single, smoker and reduced activity levels. In the final models, respondents with long-term health conditions and lower education had the strongest association with being obese or higher BMI. However, the largest impact on BMI was QoL, which provides further evidence that an increase in QoL is associated with reduced BMI.

4.6.6 Sensitivity Analysis

Table 4.14 presents the sensitivity analyses conducted. In the first analysis, a dummy variable denoting (experienced a stressful life event at some point in the past five years) was used instead of just the year prior. The results do not indicate that stressful life events prior to the year before have as much impact; therefore, a full model was not estimated. The second sensitivity analysis explored whether different types of stressful life events would be considered better instrumental variables to predict depression. Only those life events deemed to have a significant impact on an individual's likelihood of having depression were used (rather than all life events), as some life events – such as getting married, pregnancy and retirement – although stressful, have positive impacts on mental health. Each stressful life event was independently run as a regressor. The results demonstrated that personal injury, injury to a family member, being a victim of violence and a worsening of finances were good instruments to predict increased depression. This subset of life events was combined into one variable with a lag variable included to incorporate any of these life events in the preceding year. The results show that this subset of the life events are better instruments in the reduced form equation and that the effect of the event persists with time, as the lag variable is now significant. The significance of the χ^2 also indicates that there may exist some endogeneity that needs to be controlled for.

Table 4.14 Sensitivity analysis

	Model 4 (1 year lag, all stressful life events)		**SA1 (5 year lag, all stressful life events)**		**SA2 (Subset of stressful life events)**	
Obesity: predicted Model						
Depression score ≤52	1.354***	(0.072)	1.412***	(0.072)	1.180***	(0.071)
_cons	–0.816***	(0.005)	–0.826***	(0.005)	-0.810***	(0.006)
Depression: Reduced Model						
Recent SLE	0.272***	(0.011)	0.284***	(0.011)	0.350***	(0.121)
SLE in the past	0.172***	(0.010)	0.160***	(0.010)	0.219***	(0.121)
_cons	–1.372***	(0.009)	–1.416***	(0.009)	-1.321***	(0.007)
Rho	–0.605		–0.634		–0.520	
χ^2 (p-value)	165.15***		181.32***		148.70***	
Log-liklihood	–81727		–81727		–81539	
AIC	163467		166121		163090	

*Significance levels: * p<0.05; ** p<0.01; *** p<0.001*

A full model was estimated with the subset of stressful life events and controlling for all sociodemographic variable using a cmp analysis with obesity as the predicted model. The results produced larger coefficients for both the subset of stressful life events (0.251) and the one-year lag (0.110) versus 0.194 and 0.082 in the full stressful life events model presented in Model 2 (Appendix 11). This suggests that stressful life events with a greater impact on depression or mental health outcomes may be better instruments to use for a model using depression as a predictor variable for other health outcomes.

A further model was also estimated for the effect of a stressful life event on obesity under the assumption that the pathway from the stressful life event may be through poor health behaviours. Using life events as the instrument on the outcome of being a heavy drinker, the result was not significant and a full bivariate model was not estimated.

4.7 Discussion

The results from this chapter demonstrate that there is an endogeneity issue between QoL and obesity and the effect of depression may need to be modelled simultaneously with obesity to control for this. Although the results show a weak indication of endogeneity, further econometric techniques using an instrumental variable analysis with the panel nature of the data could be explored using more complex econometric techniques. There are many empirical challenges when trying to model the causal pathways of obesity. Changes in body weight fluctuate over time and are the result of a complex combination of genetic, cultural, and demographic influences. Disentangling the highly significant impact of one of these for example, the impact of long-term health conditions and mental health problems on obesity is also worthy of future research.

One limitation of these data is that weight and height estimates for the respondents only start in wave 6, possibly not providing a long enough time period for the effects of stressful life events to cause depression and thus lead to changes in weight, especially for the more recent waves. An extension to this study would be to explore not only obesity but the ordered categorical variables for the different weight classifications while exploiting the panel nature of the data using more advanced econometric techniques, such as endogeneity-switching models or fraction-response models.

The possibility of a health shock affecting mental health was also modelled as an instrument to predict depression, as the association between an occurrence of a long-term health condition and depression is highly significant, as is the association with obesity. A further subset was derived of those individuals in wave 1 who did not have a long-term health condition or were below the cut-off for depression. Although the results were highly significant for health shocks being a good instrument, the results are not reported given the uncertainty around the model estimation. Given that obesity may be the cause of many long-term health conditions and baseline obesity is not controlled for, the estimates may be biased; more complex econometric techniques are needed to estimate this complex dynamic. Furthermore, the type of long-term health condition was not available, and those conditions caused by obesity could not be disentangled from the data.

These results also imply that the effect of any of the stressful life events is more influential in the year prior to the wave as opposed to any of the prior waves. This indicates that the effect on depression is more profound in the year following the stressful life event. Prior studies also show that the effect of stressors dissipates with the passage of time (Tennant, 2002). However, this result may only hold for particular stressful life events. In the model where only injury, violence and a worsening in finances were included, the effect of these stressful life events (regardless of when they occurred) were more significant than the models that included all stressful life events. This may indicate that the effects on depression persist more for particular stressful life events and these stressful life events could have a greater impact on future weight changes.

The use of an IV analysis can have major limitations if the instrument used in the analysis is weak. If the instrument does not explain much of the variation in the treatment variable, or if the instrument is slightly correlated with the unobserved causes of y, the estimates may produce misleading results (Auld & Grootendorst, 2011). It is possible that some of the stressful life events included in the models affect BMI or obesity through means other than a direct impact on QoL. The sensitivity analysis attempted to mitigate this by only including stressful life events that, in the preliminary analysis, had no association with BMI or obesity. Also, any stressful life events that may be caused by depression, such as being fired or a worsening in finances, need to be excluded. The advantage of the stressful life events as an instrument, however, is that they demonstrated a high correlation with QoL. There is scope to investigate other instruments that may be better predictors of depression or QoL. Previous research has used parental BMI as an instrument; however, the outcomes in question were labour market factors and self-rated health.

If the model for obesity has a positive feedback loop between depression/QoL and obesity, this deserves more attention, especially at a public health level, where current obesity interventions may not be targeting the aetiology of the disorder and the interventions may not be as effective as current evaluations suggest. Given this reverse causality, reducing an individual's weight may reduce the impact of obesity on depression, but this does not imply the elimination of the underlying depression, which may persist and continue to affect QoL, even after a significant weight loss. Targeting mental health issues that arise due to stressful life events or other reasons may be important in reducing obesity.

For individuals considered at ‘high risk’ of unhealthy behaviours, it is possible that the effect on obesity is mediated through changes in these behaviours that existed before the stressful life event occurred (Deb et al., 2011). This may not be captured in the model used here, as high-risk behaviours prior to experiencing a stressful life event were not identified. Stratifying the group by those deemed at high risk for unhealthy behaviours may show a stronger association between depression and obesity.

Overall, the results indicate that the effect of stressful life events on obesity may manifest through changes in an individual’s mental health and the onset of depression. There may be an opportunity to identify people at high risk for stressful life events or depression to assist in preventing future obesity; however, more analysis is needed to model the complex network between behavioural and psychological impacts of stressful life events on depression and obesity and the positive feedback loop that exists. Treatment of obesity and mental health may need to be integrated to have a bigger impact on the growing number of overweight and obese individuals.

5 PREFERENCES FOR WEIGHT-LOSS PROGRAMS – A DISCRETE CHOICE EXPERIMENT

This chapter explores how discrete choice experiments (DCEs) can be used to understand whether obese individuals have distinct (and different) preferences for weight-loss programs when compared to normal weight individuals. It is generally accepted that overweight and obese individuals make different choices regarding food and physical activity (Cha et al., 2016; Mela, 2012). However, given the lack of success in reducing the number of obese and overweight people, it is plausible that policies aimed at reducing obesity do not fully reflect the needs or preferences of obese individuals. To test our understanding of these preferences, DCEs could be used to design and predict the uptake and overall success of weight-loss programs.

5.1 Introduction

Economists have traditionally relied on real-life consumption behaviour (for example, choice of health care provider) in order to determine individuals' preferences for a particular good or service (Lancsar & Louviere, 2008). However, several issues make the use of revealed preference (RP) data more difficult in the field of health economics.

- Revealed preference data will not be available for new interventions and programs.
- Attributes of the intervention or program may be correlated and therefore difficult to assign a value to – for example, higher prices may be perceived to mean better quality (Rohr, 2006).
- It is difficult to control for individual characteristics and attributes of choices. For example, if a patient chooses treatment A from two treatments that differ in terms of efficacy, side-effects and cost, it is unclear what factor most influenced their decision (Bridges et al., 2007).

Stated preference (SP) methods provide an alternative approach to explore the preferences of individuals. DCEs (commonly called choice experiments) are a type of SP method used to elicit individual's preferences by comparing trade-offs between a set of products/services. DCEs collect data on what individuals say they would do, as opposed to observing what they actually do (as with RP data). DCEs are based on Lancaster's economic theory of value, according to which individuals derive utility from the main attributes of a good, and preferences (and thus utility) across goods are revealed through their consumption choices (Lancaster, 1966). There is evidence that the DCE approach is consistent with welfare theory and choices observed in real life (Lancaster, 1966; Lancsar & Savage, 2004; Ryan & Gerard, 2003). In a choice experiment, respondents choose their preferred alternative from a series of hypothetical choice tasks, where each alternative is described by a number of attributes and each attribute has multiple levels, which differ across choice tasks (Ryan et al., 2006). Choosing between goods with differing attributes is an easy task for respondents to comprehend, which is a strength of the DCE approach. Furthermore, if cost is included as one of the attributes, DCEs can estimate respondents' willingness to pay for a change in an attribute level.

Choice experiments are widely used in transport economics, environmental economics, marketing and health economics (Green & Srinivasan, 1990; Hensher, 1994; Louviere, 1988; Wittink & Cattin, 1989). They are particularly valuable when revealed preference data are unavailable or do not provide sufficient variability to allow for the estimation of policy-relevant impacts. The advantages of DCEs are that the preferences for all relevant attributes can be estimated individually. Moreover, by using the sociodemographic information of the respondents, heterogeneity in the population can be explored.

DCEs need to be carefully designed and piloted, since a missing attribute that would influence a respondent's choice may bias the estimated model. Furthermore, misspecification of the model may lead to inaccurate assessment of attribute levels (Bridges et al., 2007). Although some scepticism regarding SP methods still exists, the literature supporting the use of DCEs is abundant (Louviere et al., 2000). An example of a discrete choice experiment is illustrated in Figure 5.1. This example shows the choice between two different lifestyles scenarios, with six attributes presented with different levels.

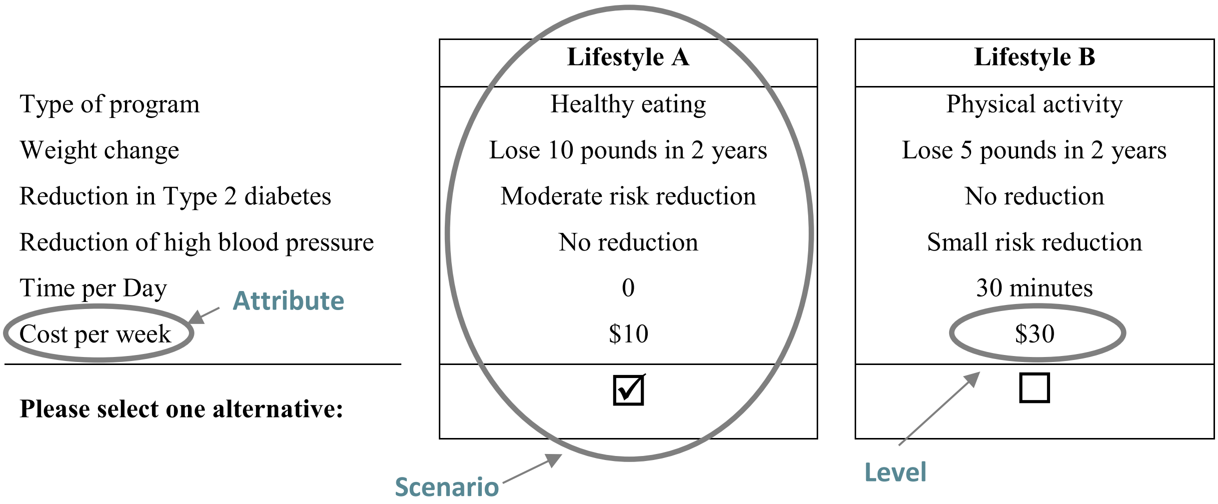


Figure 5.1 Example of a hypothetical DCE choice set

Assuming that the DCE has been properly designed, it is possible to determine the following from the analysis of SP data.

- *The relative importance of each attribute*: DCEs provide information regarding how important the levels of an attribute are (whether it is statistically significant), the relative importance of levels of the attributes (size of the coefficient) and whether any levels of an attribute are undesirable (a negative coefficient).
- *Trade-offs*: DCEs can estimate the value that people place on attributes and the trade-off between the different attributes. It allows the determination of how much of one attribute individuals are willing to give up for a gain in another attribute. By including cost within the DCE choice set, the analyst is able to estimate the individual's willingness to pay for an improvement in another attribute.
- *Probability of up-take*: By including opt-out alternatives, DCEs can be constructed to determine how likely it is that the options presented would be chosen under the hypothetical scenarios.

5.1.1 Theoretical framework

The foundations of choice models lie in the theory of demand developed by Lancaster (1966). The theory states that, when faced with several choices, individuals will choose the option that maximises their utility. This can be further refined, such that individuals derive utility from the underlying attributes of the good or service (Lancsar & Louviere, 2008). Random utility theory, in particular the random utility function, provides the framework to analyse the choices individuals make in DCEs (McFadden, 1974). The assumptions that underpin random utility models (RUMs) follow from Thurstone's Law of Comparative Judgement (Hofacker, 2007):

1. The choice the individual makes is a discrete choice (i.e., the choice leaves them with 1 unit of their preferred good and 0 of the alternative).
2. The utility derived from a choice varies across individuals and is assumed to be random.
3. The individual chooses the option that provides the greatest utility for them.

The random utility (U) of individual (i) who is faced with j number of alternatives can be described as:

$$\boldsymbol{U_{ij} = V_{ij} + \varepsilon_{ij}} \quad (5\text{-}1)$$

where V_{ij} is the indirect utility function [(V(x_{ij}, z_i)] which includes a vector of observable attributes (x_{ij}) of the alternative and a vector (z_i) of observable characteristics of the individual i (systemic component) and ε_{ij} is the error term that contains all the unobserved variables that affect choice (random component). Individuals will compare the utilities for each of the j alternatives and choose the alternative that yields the highest level of utility. For each attribute it is possible to estimate part-worth utilities, or the utility associated with each level of the attribute defined within the product or service. The probability that an individual i decides in favour of alternative j is denoted by:

$$\begin{aligned} \boldsymbol{P(Y_i = 1)} &= \boldsymbol{P(U_{ij} > U_{ik})} \quad (5\text{-}2) \\ &= \boldsymbol{P(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik})} \\ &= \boldsymbol{P\big(V_{ij} - V_{ik} > \varepsilon_{ik} - \varepsilon_{ij}\big)\ \forall k \neq j} \end{aligned}$$

This equation represents the probability of an individual choosing alternative j, given that the utility of alternative j is greater than the utility associated with alternative k after assessing each attribute. $Y_i = 1$ indicates that the individual i has chosen alternative j and $Y_i = 0$ indicates that the individual i has not chosen alternative j.

The model is then completed by assuming $V_{ij} = \beta X_{ij}$. The dependent variable in the model is the respondent's choice amongst the alternatives.

$$\boldsymbol{U_{ij} = X'_{ij}\beta_i + \varepsilon_{ij}} \quad (5\text{-}3)$$

where β_i is a vector of coefficients and X'_{ij} is a vector of explanatory variables. In this model, the errors are assumed to be identically and independently distributed (iid). The results are estimated with the general multinomial model (MNL), which is commonly used to model the responses from the respondents. The MNL model demonstrates the independence of irrelevant alternative (IIA), which indicates that the relative probability of choosing between two alternatives is not affected by attributes or a third alternative.

5.1.2 DCEs in health economics

DCEs are commonly used in health economics across a wide range of health-related concerns (Ryan et al., 2008). The International Society of Pharmacoeconomics and Outcomes Research (ISPOR) taskforce has noted that the past two decades have seen a rapid increase in the use of conjoint analysis[42] across a multitude of topics, including: (1) patient preferences for health status; (2) health care interventions; (3) pharmaceutical treatment; (4) therapeutic devices; (5) diagnostic testing; and (6) end-of-life care (Hauber et al., 2016). ISPOR also notes that the majority of these analyses have used DCE methodologies. The majority of DCEs in health economics have focused on preferences for health care products or services (Guttmann et al., 2009). DCEs may also make a valuable contribution in terms of outcome measurement for use in economic evaluations, by determining an individual's marginal willingness to pay for desired preferences (Lancsar & Louviere, 2008). There has also been considerable research into the willingness to pay for different attributes of health-related DCEs (de Bekker-Grob et al., 2012). Including a cost component in DCEs allows for this type of analysis, which may not be obtainable from revealed preference data, given that health care is often provided at low or zero cost to the patient.

5.1.3 Obesity-related DCEs

A literature search was conducted to identify published DCEs of weight-loss programs/interventions for obese people. The aim was to identify previous research questions and determine what attributes were considered important when choosing a weight-loss program. The literature search was conducted in PubMed, Medline, (Epub Ahead of Print, In-Process & Other Non-Indexed Citations) and EMBASE electronic databases, from 1996 to 1 February 2017. The search string included the following search terms: *'obesity', 'obese', 'diet*',*

[42] Conjoint analysis refers to *"any stated-preference elicitation method in which respondents are asked to rate, rank or choose from among a set of experimentally controlled profiles" (pg 4)*

'overweight' and 'discrete choice' or 'DCE', 'conjoint analysis', 'discrete choice experiment*'*. All abstracts were reviewed and relevant articles were obtained for evaluation. A further search was conducted that included the following search terms: '*BMI', 'Body Mass Index' and 'discrete choice*' or 'DCE', 'conjoint analysis', 'discrete choice experiment*'*. Studies were excluded if the focus was solely on food choices (Appendix 12).

The literature search yielded nine papers, of which six were relevant. The reference lists of the relevant articles were also searched for other relevant articles, which yielded a further two papers (Table 5.1). The ISI Web of Knowledge (www.isiknowledge.com) was also searched to identify papers that referenced any of these papers.

Table 5.1 Source of papers included in the review

Identification of papers	**N**
Studies identified through database searching	6
Studies identified through other sources (pearling)	2
Total number of records for inclusion	**8**

Overall, eight articles were identified as being important and applicable to the research question. Table 5.2 outlines the relevant papers.

Table 5.2 Discrete choice experiments for obesity

Country	N	Attributes	Levels	Results
Valuing the Benefits of Weight Loss Programs: An application of the Discrete Choice Experiment* (Roux et al., 2004*)				
Canada	158 overweight adults enrolled in community weight-loss programs	Program costs	$250, $500, $750, $1000	The 'program components emphasised' attribute resulted in the largest WTP.
		Time to travel (minutes)	Up to 15, 30, 45, 60	
		Amount of doctor involvement	None, monthly basic check-up, counselling every 2 weeks	
		Program components emphasised	Diet only, diet and exercise, diet/exercise and self-management	
		Focus of program	General group, group-specific, personal	
***Individual preferences for diet and exercise programs: changes over a lifestyle intervention and their link with outcomes* (Owen et al., 2010)**				
Australia	55 patients with metabolic syndrome (participants in 16-week trial)	Cost	No additional cost, $15/week	A shift from structured (individually designed and supervised) to flexible (self-directed) preferences of weight-loss programs over the 16-week trial from baseline. Cost became a significant factor for those who gained weight in the intervention.
		Support	Fortnightly/monthly, 4 or 6 monthly checks by health specialist, or a health club/community centre	
		Exercise duration	3h/week, 30min/day, 5h/week, 45min/day	
		Exercise structure	Self-directed and unsupervised, individual exercise under a set programme designed by an instructor, informal arrangements with friends or exercise group, commitment to a structured group-based programme.	
		Diet	Daily meal plan based on calories/government recommendations, weekly meal plans with a range of options, no targets and no fixed menus but small adjustments in quantities and types of food	
		Outcome	0.25kg, 0.5kg weight loss per week, no change in body shape but increased well-being and fitness, no body shape change	

Country	N	Attributes	Levels	Results
***'Pay them if it works': Discrete choice experiments on the acceptability of financial incentives to change health related behaviour* (Promberger et al., 2012)**				
UK	182 online 517 offline General population (≥18 years)	Incentive effectiveness *(compared to baseline 10%)*	5%, 10%, 11%, 20%, 40%	Grocery vouchers were preferred to cash for weight loss and effectiveness of intervention increased choice probability
		Incentive type	Standard medication, cash, vouchers for healthy groceries	
***Willingness to Pay for Obesity Pharmacotherapy* (Doyle et al., 2012)**				
US & UK	502 obese individuals (≥ 18 years)	Amount of weight loss (% of current body weight)	5%, 10%, 15%	Percentage of weight loss was most important attribute. Also, respondents preferred oral treatments that did not change existing diet and exercise routines and reduced long-term health risks.
		Treatment type (method of administration)	1 injection/week, 1 pill/day, 3 pills/day	
		Time to noticeable weight loss (weeks)	No change, small change, need close monitoring	
		Diet and exercise requirements (any changes required with medication)	No change, small change required, need close monitoring	
		Side effects of treatment	No side effects, minor gastrointestinal upset, five-point increase in blood pressure	
		Health improvements (% of future health risk reduction)	(per 1% reduction)	
		Cost of treatment per month	NR	
***Trading off dietary choices, physical exercise and cardiovascular disease risks* (Grisolia et al., 2013)**				
Northern Ireland	493 (general adult population 40–65)	Diet	Current, light, medium, high, restricted diet	Obese people more likely to do more physical activity than change diet to reduce health risks.
		Physical activity (increase in daily minutes)	Current, 10min, 20min, 30min	
		Cost (per week)	£0, £2, £5, £7, £10, £15, £18	
		Risk of cardiovascular disease (% reduction from respondent's actual risk)	40, 50, 60,75, 85	

Country	N	Attributes	Levels	Results
***Preferences of overweight and obese patients for weight loss programmes: a discrete choice experiment* (Muhlbacher and Bethge, 2010)**				
Germany	110 (overweight orthopaedic and cariological rehab patients)	Strategies for weight loss	Communicated by not in daily routines, communicated and included in daily routines	Most important aspects were coordination of care (continuous guidance, treatment, and aftercare) and individual therapy
		Variety of therapy measures available	Various therapy and leisure programs, standardised	
		Type of advice	Personal care by staff, no personal care	
		Therapy plan	Predefined, tailored individually	
		Hotel and service aspects	3-star comfortable, 2-star standard	
		Coordination and referral	Aftercare organised, no aftercare	
		Social contacts (interaction)	Group experience, no group experience	
		Technical competence (specialisms)	Specialised/Not specialised in overweight or obesity	
***Gaining pounds by losing pounds: preferences for lifestyle interventions to reduce obesity* (Ryan et al., 2015)**				
UK	504 general population (18 – 64)	Content of the program	Healthy eating (HE), HE with support, Physical activity (PA), PA with support, HE and PA, HE and PA with support	Despite evidence that dietary interventions are more effective for weight loss, respondents preferred lifestyle interventions involving physical activity.
		Weight change	No change, lose half stone, lose one stone	
		Short-term and longer-term health gains	Look better, feel better, look and feel better	
		Reduced risk of Type 2 diabetes	Reduction up to 20%, 20-40%, 40-60%	
		Reduced risk of high blood pressure	Reduction up to 25%, 25-50%, 50-75%	
		Time spent on the intervention	30,60,90, 120 minutes	

Country	N	Attributes	Levels	Results
		Financial costs	£1, £5, £10, £20	
Prioritising patients for bariatric surgery: building public preferences from a discrete choice experiment into public policy **(Whitty et al., 2015)**				
Australia	1994 (representative sample of adults)	Current level of obesity	Obesity (30–40 kg/m^2), severe obesity (40–50 kg/m^2), very severe obesity (>50 kg/m^2)	Preference to prioritise individuals who demonstrated a strong commitment to maintaining a healthy lifestyle. Little tendency to prioritise based on age.
		Obesity-related conditions	Already has obesity-related conditions, is at risk for developing obesity-related conditions	
		Age of person needing surgery	20, 35, 50 years	
		Family history	At least one parent or sibling is obese, has had weight issues since childhood	
		Chance of maintaining a substantial (at least half) reduction in excess weight	30%, 50%, 70%	
		Has shown commitment by responding to prescribed lifestyle intervention (ie, physical activity and diet)	Has maintained a healthy lifestyle plan for several months, resulting in some weight loss, however still in need of surgery Has not maintained a healthy lifestyle plans and has had no weight loss	
		Time already spent on surgery wait list	6 months, 1 year, 2 years	

5.1.4 Research questions and population studies

The aim of most studies (seven out of the eight) was to elicit preferences for weight-loss methods. Five studies compared different types of diet and exercise (lifestyle) programs (Grisolia et al., 2013; Muhlbacher & Bethge, 2013; Owen et al., 2010; Roux & Donaldson, 2004; Ryan et al., 2015), one investigated different pharmacotherapies (Doyle et al., 2012), and one study compared patients for bariatric surgery (Whitty et al., 2015). There were subtle differences between experiments; for example, Mulbacher and Bethge (2013) specifically elicited preferences for weight-loss programs in a population participating in a rehabilitation program, while the focus of Whitty et al. (2015) was to elicit the general population's preferences for prioritising bariatric surgery for hypothetical patients on a surgical wait list. The final study, by Promberger et al., (2012), was unique in that it analysed different financial incentives to promote changes to healthy behaviour and whether the effectiveness of the program improved acceptability.

The participants in Promberger et al. (2012), Ryan et al. (2014), Grisola et al. (2013) and Whitty et al. (2015) included samples of the general population, with Grisola et al. (2013) restricting the participants to those aged 40–65 years. Four of the studies included participants who were overweight or obese (Doyle et al., 2012; Muhlbacher & Bethge, 2013; Owen et al., 2010; Roux & Donaldson, 2004), with participants in two of the studies enrolled in a real-life weight loss/lifestyle intervention (Owen et al., 2010; Roux et al., 2004), while in one study participants were currently trying to lose weight (Doyle et al., 2012). Grisiola et al. (2013) included participants' current lifestyle in the choice experiment, which was a unique DCE framework in that DCE choices presented to participants were tailored based on their reported lifestyle and their cardiovascular risk calculated from questions prior to the DCE (Grisolia et al., 2013).

5.1.5 Attributes

A full list of the attributes and levels from all the studies is presented in Table 5.2. Of the five DCEs focusing on lifestyle programs, attributes for diet and physical activity were included. Four studies included a cost component (Owen et al., 2010; Roux et al., 2004; Ryan et al., 2015; Grisolia et al., 2013), three estimated willingness to pay (Roux et al., 2004; Ryan et al., 2015; Grisolia et al., 2013), two included a weight loss attribute (Owen et al., 2010; Ryan et al., 2015) and two included health benefits, such as reduction in the risk of cardiovascular disease (CVD) or Type 2 diabetes (Grisolia et al., 2013; Ryan et al., 2015). Roux et al. (2004) and Ryan et al.

(2014) also included an attribute related to time commitment . Promberger et al. (2012) included two attributes only, effectiveness of intervention and type of financial incentive.

The study by Doyle et al. (2012) included attributes relating to weight loss, health benefit and diet/exercise, but in addition included attributes specific to pharmacotherapy, such as mode of administration and side effects (Doyle et al., 2012). The study by Whitty et al. (2015) presented respondents with characteristics of hypothetical patients waiting for bariatric surgery. These characteristics included level of obesity, age of person, family history, commitment to lifestyle changes and time spent on waiting list (Whitty et al., 2015).

5.1.6 Analysis method and role of obesity

The predominant method of analysis was the multinomial logit model (MNL) (Doyle et al., 2012; Grisolia et al., 2013; Muhlbacher & Bethge, 2013; Owen et al., 2010; Ryan et al., 2015), which is the most commonly used method for analysing discrete choice data (Clark et al., 2014). Other modelling approaches included mixed-effects logistic (MXL) regression (Promberger et al., 2012) and random effects probit modelling (Roux & Donaldson, 2004). After testing the IIA assumption using conditional logit, Ryan et al (2014) used mixed logit and multinomial probit models. Whitty et al (2015) was the only study that reported the results of latent class modelling (Whitty et al., 2015).

Three of the studies classified respondents by weight category and attempted to compare preferences by weight groups. Grisiola et al (2013) categorised respondents into two groups, normal weight/underweight and overweight/obese, and used interaction terms to represent these groups within the MNL model. No statistically significant differences were found between the two groups. Roux et al (2004) also divided respondents into two groups (obese vs non-obese) and found that travel time was the only attribute that varied between groups, with obese respondents more willing to travel. Ryan (2015) also compared different weight categories, with higher compensation needed for normal weight individuals to participate in healthy lifestyle programs.

5.1.7 Summary of results

Grisolia et al (2013), Owen et al. (2010) and Ryan et al. (2014) found that respondents preferred programs that involved increased physical activity rather than reduced diet (calorie control). This finding was supported by Roux et al (2004), who found that participants preferred interventions that combined diet and exercise to those involving diet only. In terms of the program outcomes Doyle et al. (2012) found that the effectiveness of the program (i.e., weight loss) and avoiding changes to lifestyle were important, although changes to weight were not found to be important in Ryan et al (2014). Muhlbacher et al. (2013) indicated that the most important aspects of an intervention were coordination of care (continuous guidance, treatment, and aftercare) and individual therapy for patients in rehabilitation. Interestingly. Whitty et al (2015) (using a different DCE approach), noticed that people preferred to prioritise health care for patients who showed a commitment to maintain a healthy lifestyle and had lost some weight.

Four of the studies included a WTP analysis (Doyle et al., 2012; Grisolia et al., 2013; Roux et al., 2004; Ryan et al., 2015). In general, respondents were willing to pay for exercise programs, but needed compensation to accept lifestyle interventions and changes in diet. In Roux et al. (2004), participants were willing to pay for a weight-loss program that was tailored and comprehensive.

Overall, results from the current DCE literature indicate that obese respondents prefer interventions focused on physical activity versus changes in diet; a tailored therapy approach is also preferred. Furthermore, it appears that individuals need to be compensated to change their current lifestyle, which indicates that financial incentives may help. Some of the limitations of existing studies are the absence of a cost attribute or a WTP analysis, which are important when comparing results across studies.

The DCE in this chapter will improve on the previous studies by providing an in-depth exploration of respondents' willingness to pay for an intervention, particularly based on weight status (normal weight vs overweight/obese). Furthermore, this DCE will add to the current literature by estimating the trade-offs between weight-loss program characteristics and an in-depth exploration of heterogeneity. Another novel aspect is the inclusion of a QoL attribute to estimate program benefit, which has been absent from the other DCEs. By using EQ-5D profiles, the importance individuals place on improvements to QoL can be directly estimated. Detailed econometric modelling techniques and a latent class modelling approach will be conducted to offer more insights than have previously been reported in terms of individuals' preferences for weight-loss interventions.

5.2 Research Questions

The remainder of this chapter will describe the development of the survey and DCE instrument. The following questions were considered when designing the survey:

1. What features (attributes) of a weight-loss program are important to individuals?
2. When considering taking up a weight-loss program, do overweight/obese individuals have different preferences to normal-weight individuals?
3. How important are improvements in QoL to respondents?

5.2.1 Ethics

Ethical approval for the survey and DCE was obtained from the University of Technology Sydney Human Research Ethics Committee as part of the CHERE's program ethics (UTS HREC Ref. 201500135).

5.3 Survey structure

An online survey was developed using Survey Engine software (SurveyEngine GmbH – Germany, 2017). The survey was divided into the following sections: (1) sociodemographic and economic background; (2) weight-related questions, including weight and height (to calculate BMI); (3) the DCE choice sets (respondents completed nine choice sets); (4) quality of life (using the EQ-5D-5L); (5) time preference questions (discussed in Chapter 6); and (6) opinions of obesity-related public policy. A focus group was used during the development phase and early versions of the survey were piloted with a convenience sample and some necessary changes made (see Appendix 13 for further details). The pilot work demonstrated that the survey would take respondents approximately 15 minutes to complete. Table 5.3 outlines the structure of the survey and the specific chapter in which the results of the analysis will be presented.

Table 5.3 Online survey layout

Survey	Section Description	Location of results within the thesis
	Introduction to the survey	
Section 1	Sociodemographic questions	Chapter 5/6
Section 2	Weight-related questions	Chapter 5/6
Section 3	DCE (9 choice sets)	Chapter 5
Section 4	Quality of life (EQ-5D)	Chapter 5
Section 5	Public policy questions	Chapter 6
Section 6	Time preference questions	Chapter 6
	Feedback and comments	Chapter 5

The questions pertaining specifically to the time preferences and public policy questions will be discussed in the following chapter.

5.3.1 Section 1: Demographic questions

The specific questions included in the survey are provided in Appendix 14. Demographic questions were included in the survey, including age, gender, education level, income, marital status, country of birth, Aboriginal and/or Torres Strait Islander status and employment status. The answers from these questions were used to set age and gender quotas and to profile the respondents and establish representativeness relative to the Australian population. Data from these questions were also used to control for the effect of demographic characteristics on respondent's preferences and explore heterogeneity.

5.3.2 Section 2: Weight and lifestyle-related questions

Evidence from the literature and focus group sessions suggested that most individuals do not know their BMI; therefore, calculating BMI manually from height and weight information was considered more accurate than simply asking respondents to choose a weight category (Johnson et al., 2014). To do this, respondents were asked to report their height and weight so that BMI could be estimated. Respondents were asked '*What is your current weight (approximate)?*'. A drop-down list was provided ranging from '*46kg/7st 3lb and under*' to '*120kg/18st 3lb and over*', increasing in two-kilogram increments. Metric and imperial scales (Australia-specific) were used to reduce responder burden. Specific questions included in the survey are included in Appendix 15.

For estimated height, respondents were asked: '*What is your current height (without shoes, approximate)?*'. A drop-down list of heights was provided ranging from '*148cm/4'10" and under*' to '*200 cm/6'7" and over*', increasing in two-centimetre increments.

BMI was calculated by dividing body mass (in kilograms) by the square of the body height (in metres). This was then used to classify respondents into different weight groups: underweight (<18.5), normal weight (18.5–24.99), overweight (25–29.99) and obese (>30) (Johnson et al., 2014). Estimating BMI using this methodology has been successfully used previously in the HILDA survey.

As previously mentioned, people tend to inaccurately classify themselves as overweight/obese based on perceived weight. These weight misperceptions were explored by asking respondents:

'*Do you consider yourself to be: acceptable weight, underweight, overweight*' and '*How satisfied are you with your current weight*'. Respondents were also asked if they had ever been overweight.

This section also included questions relating to general health (using a five-point Likert scale from excellent to poor), existing health conditions (diabetes, health disease etc.), smoking status and alcohol consumption. Further questions relating to the respondent's experiences with weight-loss through diet or physical activity were also included; for example, respondents were asked if they were currently trying to lose weight through changes to their diet and/or exercise, how often they had tried to lose weight, and if they had ever paid to join a weight-loss program. Finally, respondents were asked how often they partake in moderate or vigorous activities. Respondents were asked to choose between '*not at all*', '*less than once a week*', '*1–2 times a week*', '*3–6 times a week*' and '*every day*'.

5.3.3 Section 3: DCE

In the DCE section, respondents were asked to complete nine choice set questions. For each choice set, respondents were asked to choose between two hypothetical weight-loss programs. An opt-out question was also included. An in-depth description of the development and the experimental design underpinning the DCE is presented in Section 5.4.

5.3.4 Section 4: Quality-of-life

In the previous chapters, health-related QoL was estimated using the Short Form 36 (SF-36) questionnaire. However, the inclusion of this 36-item instrument was considered burdensome for respondents, given the other survey questions. Therefore, respondents' health-related quality of life was assessed using the five-level EQ-5D version (EQ-5D-5L, EuroQol group). This instrument was chosen because the descriptive system consists of only five dimensions: mobility, self-care, usual activities, pain/discomfort and anxiety/depression. For consistency, the EQ-5D-5L descriptive system was also used to create QoL profiles within the DCE choice sets.

The EQ-5D-5L is widely used across a diverse range of health conditions and clinical areas and validated for all dimensions and levels (van Reenen & Jansses, 2015). The EQ-5D with five health dimensions and five levels defines 3,125 health states. Each health state is a combination of one of the five levels, indicating no problem, slight problem, moderate problem, severe problem or extreme problem. The five dimensions that the EQ-5D values are mobility, self-care, usual activities, pain/discomfort and anxiety/depression. The health states defined by the EQ-5D-5L can be transformed into utility scores, representing respondents' health-related QoL on an ordinal scale of 0 to 1 (death to full health) with values less than 0 indicating health states worse than death (Norman et al., 2013b). These utility values can also be compared to the SF-6D utility values from the HILDA survey. A copy of the questionnaire given to respondents is in Appendix 16.

5.3.5 Section 5: Public policy questions

The survey included questions of respondents' opinions of public policy surrounding the issue of overweight and obesity. These will be presented in the following chapter.

5.3.6 Section 6: Time preference questions

The survey included four time-preference questions to ascertain whether overweight or obese individuals value future costs and benefits differently to normal weight individuals. The development of these questions and analysis are presented fully in the following chapter.

5.4 Discrete Choice Experiment development

The DCE was developed following the recommendations from the ISPOR taskforce for conjoint analysis experimental design (Bridges et al., 2011). Figure 5.2 summarises the stages used during the development of the DCE to ensure that the experiment was well designed and appropriate for the research questions. Details of the full checklist are presented in Appendix 17.

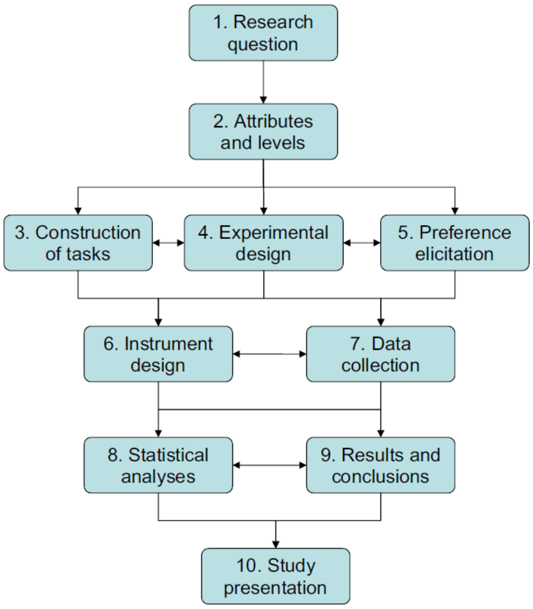


Figure 5.2 ISPOR checklist for conjoint analysis applications in health & medicine.
Source: Bridges et al., 2011.

5.5 Defining attributes and levels

An important aspect of DCEs is the choice of attributes. If there are too many attributes, it can unnecessarily burden the respondent and they may not consider all attributes when making their choice. A review of DCEs within health economics indicated that the number of attributes used ranged from two to 24, with most DCEs having between 4–9 attributes (de Bekker-Grob et al., 2015). A more recent trend (from 2009 onwards) is to include more attributes, with DCEs typically using 7–9 attributes. There is no written rule about the number of attributes a DCE should contain; DeShazo and Fermo (2002) found that by increasing the number of attributes (by analysing the effect of omitting relevant attributes), the 'cognitive burden associated with greater information outweighs the potential increase in consistency induced by a more complete description of the product's attributes' (DeShazo & Fermo, 2002). However, Louviere et al. (1997) believe that the number of attributes will not significantly alter the choices made by respondents. For the current DCE, nine attributes were chosen.

The ISPOR guidelines recommend each attribute and the corresponding levels be sourced using scientific evidence. Therefore, a literature review was conducted to inform attribute selection and the corresponding levels (described in section 5.1.3). Further changes were made to the attributes based on input from a focus group. Three distinct themes were found to be important: program characteristics, program outcomes and QoL (after the program). Table 5.4 outlines the attributes and levels included in and the direction of the preferences expected for each attribute.

Table 5.4 Attributes and levels in the DCE

	Attribute	Levels	A priori expectations
Program characteristics			
1	Type of diet	Reduced calorie diet None	A preference for programs with exercise over diet was expected
	Type of exercise	Group-based exercise Individual-tailored exercise None	
2	Duration of program	3 months 6 months 1 year	A negative preference for longer durations was expected
3	Time commitment	2 hours/week 5 hours/week 10 hours/week	A negative preference for longer time commitment was expected
4	Cost of program*	No cost $25/month $50/month $100/month	A negative coefficient was expected on the cost variable imputed as a continuous variable
Program outcomes			
5	Weight loss	0.5 kg/month 1 kg/month 2 kg/month 3 kg/month	A positive preference for higher weight loss was expected
6	Obesity-related disease risk	No reduction Lower risk of cardiovascular disease Lower risk of Type 2 diabetes Lower risk of cancer	A positive preference over no reduction was expected but no a priori expectations for which diseases
7	Appearance	Improved skin and hair Reduction in body fat Look slimmer Increased muscle tone	No a priori expectations for which appearance attributes would be preferred
8	Weight loss reward	No reward $50/month $100/month	A positive preference for higher reward amounts was expected
Quality of life (after the program)			
9	Utility value: 1.00	No problems walking about No problems doing my usual activities No pain or discomfort Not anxious or depressed	A positive preference for higher quality of life was expected
	Utility value: 0.90	No problems walking about No problems doing my usual activities Slight pain or discomfort Not anxious or depressed	
	Utility value: 0.75	Slight problems walking about Slight problems doing my usual activities Slight pain or discomfort Not anxious or depressed	
	Utility value: 0.60	Slight problems walking about Slight problems doing my usual activities Moderate pain or discomfort Slightly anxious or depressed	

**In the first pilot, the cost levels of the program were $0, $30, $100 and $300. It was decided to adjust the upper cost as it was deemed too extreme.*

5.5.1 Attribute 1 (a and b): Type of program

Most weight-loss programs work through dietary changes (reducing energy in), increased exercise (energy out) or a combination of the two. A recent meta-analysis found that exercise was more effective than diet alone, but that a combination of both was most effective (Clark, 2015). It was therefore decided to evaluate preferences for both diet and exercise weight-loss programs. A five-level attribute was created which included combinations of reduced-calorie diet/no diet with group-based exercise/individual-tailored exercise/no exercise. The five different program options were:

- Reduced calorie diet/Group-based exercise
- Reduced calorie diet/Individual-tailored exercise
- Reduced calorie diet/No exercise
- No diet/Group-based exercise
- No diet/Individual-tailored exercise.

Based on focus group feedback and to help reduce responder burden, this five-level attribute was presented in the choice set as two attributes, 'type of diet' and 'type of exercise'. The main reason for using a five-level attribute in the design was to avoid the implausible combination of 'no diet/no exercise', which would have occurred had diet and exercise been designed as two separate attributes.

It was decided that the type of diet would be kept generic, since testing preferences for specific diets was not an aim of the experiment. In the introductory vignette it was explained that any diet (whether it be low fat, low calorie, limiting junk food etc.) would result in reduced calories. The exercise program options chosen were group-based exercise, individual-tailored exercise and no exercise.

5.5.2 Attribute 2: Duration of program

Based on the Cochrane review, most weight-loss programs have an intervention period of between 12 and 52 weeks (Shaw et al., 2006). Therefore, the levels of duration were set at 3 months, 6 months and one year.

5.5.3 Attribute 3: Time commitment

The physical activity guidelines for Australia recommend 2.5–5 hours of moderate physical activity per week (Department of Health, 2014). The Cochrane review reported exercise frequency of 3–5 days a week across all studies, and the median exercise duration was 45 minutes (Shaw et al., 2006). Based on these guidelines/studies, the following time commitment levels were chosen: two hours, five hours or ten hours a week. An exercise frequency of ten hours was added to assess the impact of extreme (but plausible) time commitment on participants' choices for weight-loss programs.

5.5.4 Attribute 4: Cost of program

A cost attribute was included, partly for realism and partly to post-estimate marginal willingness to pay for the other attributes. The costs of the program were chosen to be no cost, $25/month, $50/month or $100/month. A no cost option represented a scenario in which the exercise program would be covered by a government agency or public health campaign. The $100/month represents a cost of $25/week, which was sourced from one of the largest fitness chains (Fitness First). Lower costs of $25/month and $50/month were included based on subsidised weight-loss program costs.

5.5.5 Attribute 5: Weight loss

The benefits of the weight-loss program were expressed in terms of weight loss (kg), reduction in obesity-related diseases (risk of cardiovascular disease, diabetes and cancer), a weight loss reward ($) and improved QoL.

The amount of weight loss from the program was included because it is the most frequently used measurement to assess the success of a program. The recommended amount of weight loss per month is 0.5–1 kg per week.[43] Assuming a weekly loss of 0.5kg, the monthly weight loss would be approximately 2kg. The weight loss achievements included were 0.5, 1kg, 2kg and 3kg per month. Total (or absolute) weight loss was not used because the length of the program was an attribute within the DCE, and thus implausible or undesirable totals could have occurred. The meta-analysis by Franz et al. (2007) demonstrated the largest average weight loss from

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[43] Government of South Australia: Healthy weight loss tips. http://www.sahealth.sa.gov.au/wps/wcm/connect/public+content/sa+health+internet/healthy+living/healthy+weight/healthy+weight+loss+tips

very-low-energy diets was 18kg over six months. The amount of 3kg per month was therefore used as the extreme (but plausible) weight-loss value in the experiment.

5.5.6 Attribute 6: Obesity-related disease risk

Initially, the DCE included the mortality risk associated with overweight and obesity. However, the pilot work suggested that individuals did not fully understand how this would affect their longevity. Therefore, it was decided to include a description of the likely health impacts that could be expected from losing weight. The levels chosen included no reduction (no benefit), lower risk of cardiovascular disease, lower risk of Type 2 diabetes and lower risk of cancer. These diseases were chosen because the Australian Burden of Disease Study reported that cancer, cardiovascular diseases and diabetes are the main diseases associated with overweight and obesity (AIHW, 2016b).

5.5.7 Attribute 7: Appearance

From discussions with the focus group, an attribute describing changes to one's appearance as a result of weight loss was included. The four levels assumed to be important were improved appearance of skin and hair, reduction in body fat, looking slimmer and increased muscle tone. Ryan et al. (2015) included a similar attribute, with levels including look better, feel better, look and feel better. More descriptive choices were thought to be an improvement on 'looking better', which is subjective.

5.5.8 Attribute 8: Weight loss reward

An attribute was included to test the impact of financial incentives to encourage weight loss. It has been argued that economic incentives result in better weight-loss outcomes than programs such as public health campaigns etc. (Ries, 2012). Testing this attribute will also help inform the chapter on time preferences, as people may be reluctant to change unhealthy behaviours but may respond to the immediate gratification of a financial incentive (Ananthapavan et al., 2018). The three levels chosen for the reward (no reward, $30/month, $100/month) were considered realistic and informed by the focus group.

5.5.9 Attribute 9: Quality of Life

A unique aspect of this DCE was the inclusion of a QoL health state description within the choice sets, to represent improvements to QoL as a result of a weight-loss program. Since the EQ-5D-5L instruments has a possible 3,125 unique health states, a decision on which health states to include in the DCE was needed to describe the health states most pertinent to overweight and obesity. Previous studies have found that excess weight has the greatest impact on mobility and pain/discomfort (Sach et al., 2007; Xu et al., 2015). Xu et al. (2015), found that overweight or obese women had lower (worse) mobility and pain/discomfort scores compared to normal weight women and that obese men had lower mobility scores compared to normal-weight men (Xu et al., 2015).

Using Australian QoL population norms, four utility values representing full health (1.00), normal weight (0.90) overweight (0.75) and obese (0.60), were chosen (Norman et al., 2013a). These utility values were then matched to distinct health states using the Australian algorithm for the EQ-5D-5L (Norman et al., 2013a). This study provides the utility decrement for each level within each EQ-5D dimension.[44] For example, to obtain a utility value of 0.90 (age-adjusted normal weight), a utility decrement of 0.08, which corresponds to slight pain or discomfort, was subtracted from full health (1.00). This results in a utility value of 0.92 which is the closest value to 0.90 that can be estimated from the EQ-5D algorithm. Utility values for overweight and obese were derived using the same process[45].

During the focus groups session, it was decided that obese individuals could plausibly have difficulties with pain, mobility, usual activities and depression, but that it was unlikely that self-care would be an issue. This view was supported by Xu et al. (2015), who showed that the self-care dimension had the lowest association between BMI and QoL. To lessen responder burden, the self-care dimension was removed from the experiment (Xu et al., 2015).

Table 5.5 displays the four health states chosen for the DCE and the corresponding EQ-5D dimension levels.

[44] Model D in the Norman (2013) study was used to apply the decrements to full health.

[45] The decrements for overweight were 0.072 (mobility), 0.116 (usual activities) and 0.079 (pain/discomfort). The decrement for obese were 0.072(mobility) 0.116 (usual activities), 0.089 (pain/discomfort) and 0.14 (anxiety/depression)

Table 5.5 EQ-5D health states for DCE

Health States	EQ-5D dimension	Decrement^	Utility value
Full Health	No problems walking about No problems doing my usual activities No pain or discomfort Not anxious or depressed	– – – –	1.00
Normal weight	No problems walking about No problems doing my usual activities Slight pain or discomfort Not anxious or depressed	– – 0.079 –	0.92
Overweight	Slight problems in walking about No problems doing my usual activities Moderate pain or discomfort Slightly anxious or depressed	0.072 – 0.116 0.079	0.73
Obese	Moderate problems in walking about Slight problems doing my usual activities Moderate pain or discomfort Slightly anxious or depressed	0.072 0.116 0.089 0.14	0.58

^ Source: Norman et al., 2013a. Note: the 'self-care' dimension has been excluded as it did not change for the four utility values.

5.5.10 Omitted variable bias

It is recommended that qualitative methods be used to inform the DCE process – specifically, the selection of attributes (Clark et al., 2014). A literature search was initially conducted, and this was supplemented by information from a focus group discussion. The focus group was a convenience sample (n=25) that provided feedback on the attributes and levels. The main intention of this is to mitigate any potential omitted variable bias (see **Appendix** 13 for further details).

5.6 Construction of tasks

The construction of tasks refers to the justification of the number of attributes chosen, specifically a partial or full profile and whether the number of profiles is justified. A full profile, in which all attributes would vary across all levels (Sun, 2012), was chosen. However, given the aim of allowing for interactions between costs and rewards, there were scenarios in which the cost was the same between program options. Cost was the only attribute that might not differ between options in a choice set.

5.6.1 Opt-out or status-quo scenario

As the DCE was designed to elicit preferences for obesity interventions, an opt-out option was included to represent a real-world scenario (Veldwijk et al., 2014). Allowing respondents to opt-out helps identify those individuals who are 'policy inelastic'; in other words, individuals who do not wish to change their current behaviour or weight. In order to ensure that individuals did trade-off between choice sets, the opt-out question was asked after each DCE choice set:

- If you were overweight and the program you chose were available would you:
    - Enrol in program
    - Do nothing.

It was decided that using this approach would improve efficiency, since the opt-out would allow estimation of the proportion of respondents unlikely to enrol in weight-loss programs.

5.7 Preference elicitation

Before the DCE choice task, a set of instructions was provided (Box 5.1). The purpose was to explain the rationale for the DCE and provide respondents with relevant information about obesity and QoL. The questionnaire and DCE were piloted with a convenience sample to test for comprehensibility and format.

Box 5.1 DCE instruction page

In the following section we are interested in how people who are overweight choose weight loss programs. You will be asked to choose between 2 weight loss programs based on the following characteristics:

- Type of diet/exercise
- Time commitment
- Cost of program
- Weight loss expected
- Obesity-related disease risk
- Appearance
- Weight-loss reward
- Quality of life changes

Being overweight is associated with an **increased risk** of developing a number of health problems, including **heart disease, Type 2 diabetes, osteoarthritis and some cancers.**

People that are overweight may also have a **lower quality of life**. A typical quality of life profile would be:

- **Mobility** - slight problems in walking about
- **Usual activities** - slight problems doing usual activities
- **Pain/discomfort** - moderate pain or discomfort
- **Anxiety/depression** - slightly anxious or depressed

Losing weight and eating healthy can reduce the risk of obesity-related illness and improve the person's quality of life.

Please complete the following **9 questions**.

Figure 5.3 presents an example of one of the choice sets. Respondents were asked the following:

- *Imagine that you are overweight, and you would like to lose weight.*
- *You have been invited to enrol in a weight-loss program. The characteristics and benefits of the 2 programs are described below.*
- *Please indicate which of the two programs you prefer.*

After choosing their preferred program, respondents were asked the follow-up question, '*If you were overweight and the program you chose were available would you: 1) enrol in the program or 2) Do nothing'*. Respondents were required to answer the follow-up question before proceeding to the next vignette.

Program characteristics	**Program 1**	**Program 2**
Type of diet	Reduced calorie diet	No diet
Type of exercise	Individual-tailored exercise	Group-based exercise
Duration of program	3 months	6 months
Time commitment	10 hours / week	5 hours / week
Cost of program	$50 / month	No cost
Program outcomes		
Weight loss	3 kgs / month	2 kgs / month
Obesity-related disease risk	No reduction	Lower risk of cardiovascular disease
Appearance	Increased muscle tone	Look slimmer
Weight loss reward	No reward	$100 / month
Quality of life (after the program)		
Mobility	No problems walking about	Slight problems walking about
Usual activities	No problems doing my usual activities	Slight problems doing my usual activities
Pain / discomfort	No pain or discomfort	Moderate pain or discomfort
Anxiety / depression	Not anxious or depressed	Slightly anxious or depressed
Which program would you choose?	○ Program 1	○ Program 2

If you were overweight and the program you chose were available would you?
○ Enrol in the program ○ Do nothing

Figure 5.3 DCE Vignette

5.7.1 Task comprehension

Each respondent completed nine different choice sets, comprising eight designed choice sets and one dominant choice set. A study conducted to assess the impact of varying the number of choice sets based on model parameter and variance found that the number of choice sets (5, 9 or 17) had little bearing on the overall conclusions; however, the findings did indicate that respondents may experience fatigue as the number of choice sets increases (Bech et al., 2011). Eight choice sets were chosen for this study to reduce respondent fatigue, given that respondents were also asked to complete a number of other survey questions. The ninth choice-set was a dominant choice set, in which the attribute levels in Program 2 were always better than or equal to the attribute levels in Program 1 (Figure 5.4). For example, Program 2 had the same components (no diet/group-based exercise) as Program 1 but cost nothing. Program 2 also had a reduction in disease risk, rewards of $100 a month and better quality of life compared to Program 1. This choice set was programmed directly into Survey Engine and the data collected separately from the other choice tasks. The dominant choice set was used to test comprehension and as a proxy for irrational responses. During the sensitivity analysis, respondents who chose Program 1 (the dominated option) in this choice set were excluded from the analysis.

Program characteristics	**Program 1**	**Program 2**
Type of diet	No diet	No diet
Type of exercise	Group-based exercise	Group-based exercise
Duration of program	6 months	6 months
Time commitment	5 hours / week	5 hours / week
Cost of program	$100 / month	No cost
Program outcomes		
Weight loss	2 kgs / month	2 kgs / month
Obesity-related disease risk	No reduction	Lower risk of cardiovascular disease
Appearance	Look slimmer	Look slimmer
Weight loss reward	No reward	$100 / month
Quality of life (after the program)		
Mobility	Slight problems walking about	No problems walking about
Usual activities	Slight problems doing my usual activities	No problems doing my usual activities
Pain / discomfort	Moderate pain or discomfort	No pain or discomfort
Anxiety / depression	Slightly anxious or depressed	Not anxious or depressed
Which program would you choose?	○ **Program 1**	○ **Program 2**

If you were overweight and the program you chose were available would you?

○ Enrol in the program ○ Do nothing

Figure 5.4 Dominant choice set vignette

5.8 Experimental Design

It is important when designing a DCE to obtain unbiased parameter estimates. Multiple methods are available to construct DCE designs: (1) statistical software, such as SAS and Stata, have algorithms available to construct DCE designs, (2) there exist multiple catalogues of orthogonal designs, and (3) software packages such as Ngene and Sawtooth are available (Reed Johnson et al., 2013). It was decided to use a Street and Burgess D-efficient design (Street & Burgess, 2007). These designs are optimal for generic, forced-choice, main-effects models (or a specified subset of two-factor interactions) and models with any number of alternatives, attributes or levels (Reed Johnson et al., 2013). Street and Burgess designs have been used in numerous published DCEs (de Bekker-Grob et al., 2012; Lancsar & Louviere, 2008; Reed Johnson et al., 2013).

In this DCE, nine attributes were chosen: one five-level, three three-level and five four-level attributes. This resulted in a full fractional design that includes a total of 138,240 possible options (5^1 x 3^3 x 4^5). The number of possible choice sets of size 2 from this set of profiles is [(138,240 x 138,239/2) = 9,555,079,680]. Obviously, it would be impossible to present all possible choice sets within the survey. To reduce the number of choice sets for each participant, a subset of the complete set of pairs is chosen. (Some authors erroneously refer to this as a fractional factorial design, but it is in fact an incomplete block design with blocks of size 2.)

5.8.1 Main effects and interactions

It is common in DCE design to only consider main effects, since these effects explain most of the variation in preferences (de Bekker-Grob et al., 2012). The main effect is the effect of each attribute (independently) on the response variable (i.e., choice of weight-loss program). The design for this DCE incorporated both main effects and one interaction. An interaction term was included in the design to allow for the simultaneous effect of both the cost of the program ($) and weight-loss rewards ($) on the choice of alternative. It was assumed that, rather than take into account their preferences for cost and rewards independently, respondents would calculate the net cost of the program ([cost of program] – [reward for participation in program]) and that the result of such a calculation would influence their choice of program. No other interactions were considered in the design.

5.8.2 Efficient designs

The aim of efficient designs is to reduce the standard error of the parameter estimates, prior to conducting the survey. Efficient designs are informed by prior information about parameter estimates and the asymptotic variance–covariance (AVC) matrix. The prior estimates are the best guess of the true parameter values and the AVC approximates the true variance–covariance matrix. The AVC assumes a large sample size or a large number of repetitions using a small sample and is dependent on the design, choice observations, parameters and the number of respondents. Efficient designs can be assessed by D-error (determinant of AVC matrix) or the A-error (trace of the AVC matrix). It was decided that the most appropriate design was a

D-efficient design, provided by Professor Deborah Street (University of Technology Sydney) (Street, 2017).

5.8.3 Priors

Efficient designs assume that an AVC matrix can be determined with prior data (either from other studies or pilot studies) informing the coefficients. Given that the parameter (β) values are unknown, $\hat{\beta}$ are used as best estimates of the true parameter values. Within efficient designs the aim is to derive an AVC with the lowest efficiency measure (which measures the design's inefficiency). The D-error is most commonly used, and a design with the lowest D-error is called *D-optimal.* These D-optimal designs allow for more precise estimates of β (Louviere et al., 2008). DCEs are restricted by the number of choice questions given to respondents, and efficient designs maximise the precision of the estimated parameters in the choice model (Reed Johnson et al., 2013). There are three scenarios that an efficient design can predict:

1. No prior information available (D_z-error)
2. Prior information available with good approximations of β
3. Prior information available but uncertainty around approximations of β.

It could be argued that there would never be a case to use the second scenario, as there will always be some uncertainty around priors.

5.8.4 Simulations

In order to evaluate the efficiency of the design, a number of simulations were run in RStudio[46] (a programming software for statistical computing), with code provided by Street (2017). The efficient design provided by Street (2017) included both 72- and 144-choice set samples. Simulations were run to evaluate the efficiency of the design by altering the number of participants[47] (determined by the estimated sample size needed for the survey) and the number of simulations.[48] Four different sets of priors were used to in the simulations to test the efficiency: (1) zero priors, (2) random priors, (3) direction of priors based on assumed direction and (4) priors based on the literature review. Table 5.6 displays the four sets of prior values used in the simulations.

[46] https://www.rstudio.com/
[47] The number of participants tested was 20 and 100 for the 72 choice set and 10 and 50 for the 144 choice set.
[48] The number of simulations tested ranged from 10, 100 and 100.

Table 5.6 Efficiency simulations

Attribute	Levels	Coefficient	Priors(1)	Priors(2)	Priors(3)	Priors(4)
Duration	3 months	–	–	–	–	–
	6 months	β_1	0	0.1	–0.1	0
	1 year	β_2	0	0.1	–0.1	0
Time	2 hours/week	–	–	–	–	–
	5 hours/week	β_3	0	–0.1	–0.2	–0.1
	10 hours/week	β_4	0	0.1	–0.2	–0.2
Weight loss	0.5 kg/month	–	–	–	–	–
	1 kg/month	β_9	0	–0.1	–0.1	0.05
	2 kgs/month	β_{10}	0	0.1	–0.1	0.1
	3 kgs/month	β_{11}	0	–0.1	–0.3	0.2
Disease risk	No reduction	–	–	–	–	–
	Lower risk of cardiovascular disease	β_{12}	0	0.1	–0.2	0.1
	Lower risk of Type 2 diabetes	β_{13}	0	0.1	–0.1	0.1
	Lower risk of cancer	β_{14}	0	0	–0.1	0.1
Appearance	Improved hair and skin	–	–	–	–	–
	Reduction in body fat	β_{15}	0	0.1	–0.3	0
	Look slimmer	β_{16}	0	–0.1	–0.2	0
	Increased muscle tone	β_{17}	0	0.1	–0.1	0
Quality of life	Utility value – 0.60	–	–	–	–	–
	Utility value – 0.75	β_{18}	0	0.1	–0.2	0.05
	Utility value – 0.90	β_{19}	0	0	–0.2	0.1
	Utility value – 1.00	β_{20}	0	0.1	–0.3	0.2
Cost and Financial rewards	Cost $0, reward $0/month	–	–	–	–	–
	Cost $0, reward $50/month	β_{21}	0	0	–0.2	0.1
	Cost $0, reward $100/month	β_{22}	0	–0.1	–0.1	0.2
	Cost $30, reward $0/month	β_{23}	0	0	–0.1	–0.1
	Cost $30, reward $50/month	β_{24}	0	0.1	–0.3	0.05
	Cost $30, reward $100/month	β_{25}	0	0.1	–0.3	0.1
	Cost $100, reward $0/month	β_{26}	0	0.1	–0.2	–0.15
	Cost $100, reward $50/month	β_{27}	0	0.1	–0.1	–0.5
	Cost $100, reward $100/month	β_{28}	0	0	–0.2	0
	Cost $300, reward $0/month	β_{29}	0	–0.1	–0.3	–0.2
	Cost $300, reward $50/month	β_{30}	0	0	–0.3	–0.15
	Cost $300, reward $100/month	β_{31}	0	0.1	–0.1	–0.1

The simulation results provide an estimate of the coefficients and the standard errors. In Appendix 18, a sample of the simulation output is presented. In this simulation, 100 iterations were run for 50 subjects, using the third set of priors. As can be seen from the estimated βs, the coefficients are very similar to the priors. Also, the standard errors for all the dimensions (except for cost and rewards) are quite small. The high standard errors for the interactions terms between cost and reward are expected, given that the replication for these parameters is less than is required for main effects only.

A further test of the design was conducted in Stata. A conditional logit model was used, resulting in only two of the 31 coefficients being significant. Using a significance level of 0.05, it would be expected that 1.5 of the coefficients would be significant. After comparing the outputs of the simulations from the 72 and 144 outputs, it was decided to use the 144-choice set in the data.

5.9 Instrument design

An online survey was used for the ease and timeliness of obtaining respondents and data. The use of online surveys is a common approach to collect DCE responses and has been successful in previous DCEs conducting health economic research (Goodall et al., 2017; Parkinson, 2013; Norman et al., 2013b; King et al., 2006; Knox et al., 2013).

5.9.1 Survey Engine

The DCE was constructed in Survey Engine[49] (2017), an online survey software specifically designed for choice experiments. All the survey questions and choice sets were manually entered into the software. The DCE design was also programmed into Survey Engine with changes to the in-built design inputted using the design by Street (2017). Final design changes to the DCE were aided by support from Survey Engine. The software was provided free of charge during the development of this chapter. This was part of a collaboration to enable Survey Engine to develop a new version of their software.

5.10 Data Collection

5.10.1 Sample size

It was estimated that to be able to calculate main effects and the interaction between cost and rewards, a minimum sample of 1200 respondents would be needed. Quotas were set to ensure the sample was representative of the Australian population, particularly in terms of the proportion of overweight/obese respondents. An Australia-wide online panel provider was engaged to administer the DCE to 2,000 respondents. Oversampling was used to account for incomplete and implausible answers (i.e., those individuals who fill out the survey without following directions).

[49] https://surveyengine.com/index.html

5.10.2 Online panel

Respondents were recruited using Pureprofile (www.pureprofile.com/au/), an online panel provider with over one million panel members. Pureprofile recruits respondents through various online and offline sources and validates recruitment through identity validation, IP address matching, name matching, profile matching and unique machine ID validation. If respondents are identified as giving nonsensical responses or speeding through surveys, they are removed from the panel after three offences. Respondents were invited to participate via an email link which granted access to the survey. In order to attract respondents, Pureprofile offers respondents a small sum that is paid upon completion of the survey. Respondents were recruited to be representative of the general population of Australia (18 years and older) by age and sex. Recruitment took approximately one week. The first draft of the survey was completed by a convenience sample of 10 respondents. Three pilot samples were collected, with essential changes made prior to collecting the full sample. Details of the pilot data can be found in Appendix 13.

Full sample

The full sample was collected between 25 August and 6 September 2017 using the Pureprofile panel. Table 5.7 describes the various samples collected during the pilot and final stages of the survey sampling.

Table 5.7 Survey samples

	Description	Main changes to survey	Total respondents	Number of non-respondents	Number of respondents
Sample 1	Convenient sample at CHERE	First draft for feedback	10	0	10
Sample 2	Pilot 1 – Pureprofile	Minor updates and height and weight question reformatted	117	13	104
Sample 3	Pilot 2 – Pureprofile	Maximum cost level changed to $100, QoL question fixed, dominant strategy changed	119	17	101
Sample 4	Pilot 3 – Pureprofile	Ngene design,	138	17	121
Sample 5	Full sample	Time preferences questions updated	1780	283	1497
Total respondents			**2163**	**330**	**1833**

5.10.3 Feedback questions

Respondents were asked to rate how difficult they found the task (ranging from 1 to 10), to assess task comprehension or overall difficulty of the survey. The respondents also had the opportunity to provide comments in an open text box.

5.11 Data analysis

5.11.1 Cleaning the data

For the final dataset, duplicate entries and data created during the development of the survey were deleted. Variables containing string data were converted to numeric format for the data analysis. A dummy variable was created to denote a 'DCE completer', which included all respondents from Pilot 2 and the full sample who completed the survey plus those who completed the DCE questions.

5.11.2 Statistical analysis

All analyses were performed using version 15 of Stata®. A summary of the statistical methods used is presented in Table 5.8.

Table 5.8 Statistical analyses

Section	Outcomes	Method
Section 1	Demographics	Categorical variables: frequency, percentages
Section 2	Weight-related questions	Continuous variables: Mean, standard deviation, minimum and maximum
Section 3	Quality of life (EQ-5D)	Summary utility scores using EQ-5D-5L algorithm
Section 4	DCE (8 choice sets)	Preference weights: CLM Preference heterogeneity: MXL, G-MNL, LC Willingness to pay: marginal rate of substitution Sensitivity analysis: CLM

CLM: conditional logit model; MXL: mixed logit model; G-MNL: generalised multi-nominal logit; LC: latent class model

Demographics summary statistics

For each of the demographic questions (gender, age, birth country, Aboriginal or Torres Strait Islander origin, marital status, income and employment), the number of respondents and proportions were calculated. These results were compared to the Australian population using

ABS information and data from Australian Demographic Statistics (2017),[50] the General Community Profile from the 2016 census[51] and the National Health Survey (2014–15)[52].

Health and weight-related summary statistics

Using the equation of [weight(kg)/height(m^2)], BMI was calculated for each respondent. The mean weight and height were calculated for males and females. The BMI values were then used to classify respondents into weight categories using the WHO classifications (as presented in Table 1.1). Respondents were classified as underweight, normal weight, overweight obese or severely obese. The number of respondents in each weight category and the proportions were calculated. For all other health-related questions, the number of respondents and proportions were calculated.

Quality-of-life utility scores

To calculate the QoL utility values for each respondent, the data collected from the EQ-5D-5L were converted to utility values using an Australian algorithm from Norman et al. (2013).

Five new variables were created to represent the five dimensions of the EQ-5D-5L (mobility, self-care, usual activities, pain/discomfort, depression/anxiety). Then, for each respondent, a decrement was calculated based on the level they recorded, using Model D provided in Norman et al. (2013a). For example, if a respondent reported 'slight problems in walking about', a decrement of 0.072 was applied to the mobility dimension. For dimensions at the highest health level (i.e., no problems), no decrement was applied. To calculate the respondents' overall utility, the decrements for each dimension were subtracted from 1 (full health). Finally, if the respondent reported the most severe health state for any dimension, a further decrement of (0.059) was subtracted; this is often referred to as the N5 adjustment.

Once the utility values were derived, the mean, 95% CIs and the range were calculated for all respondents and categorised by gender, weight categories, health status and ongoing medical conditions. The number of respondents reporting each of the five levels in the dimensions was also calculated, as was the overall distribution of the mean EQ-5D-5L score across all

[50] Demographic statistics data file: http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3101.0Sep%202017?OpenDocument

51 2016 census data files: http://www.censusdata.abs.gov.au/census_services/getproduct/census/2016/communityprofile/ 036?opendocument

52 NHS 2014-15 data files (Table 8): http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/4364.0.55.0012014-15?OpenDocument

respondents. Adjusted mean EQ-5D-5L scores were calculated by OLS regressions, controlling for demographic variables for each of the BMI weight categories.

5.11.3 DCE Preference weights

The statistical models used to analyse the respondents' choice data from the DCE are provided in Table 5.9.

Table 5.9 Statistical models used in the DCE analysis

Model	Statistical Method	Description	STATA Command[53]
Model 1	Conditional logit	• Assumes respondents have same preferences • IIA property	clogit
Model 2	Latent class	• Assumes coefficients are discrete • Each individual is assumed to belong to class *q* and preferences vary across classes (and not within classes)	lclogit
Model 3	Mixed logit	• Allows for preferences to vary across individuals • IIA property relaxed	mixlogit
Model 4	Generalised multinomial logit	• Allows for preferences to vary across individuals and preferences more random for some individuals • IIA property relaxed	gmnl
Model 5	Willingness to pay	• Estimate marginal trade-offs	wtp/nlcom

For each attribute, dummy variables were coded using factor variable coding in Stata. The only exception was the cost attribute, which was included in the model as a continuous variable. All models controlled for intragroup correlation by specifying the standard errors to allow for clustering around each respondent. This specifies that the choice sets are independent across clusters (respondents) and relaxes the assumption that observations are independent. Clustering around the respondents only affects the estimated standard errors and not the estimated coefficients (Stata.com).

Logit models have largely been replaced as the use of multinomial logit models (MNL) has increased. The conditional logit model (CLM) is the most widely used MNL analysis method, and is the usual starting model for analysis of choice models given the link to random utility theory (Lancsar et al., 2017; Louviere & Lancsar, 2009). CLMs are simple to run and interpretation of the estimated coefficients is intuitive (Cheng & Long, 2007). CLMs are based on the assumption of independence from irrelevant alternatives (IIA). This imposes the

[53] https://www.stata.com/manuals13/rclogit.pdf, https://www.stata-journal.com/sjpdf.html?articlenum=st0133, https://ageconsearch.umn.edu/record/243203/files/sjart_st0301.pdf, https://www.stata-journal.com/sjpdf.html?articlenum=st0312, https://www.uib.no/filearchive/wp-0310_2.pdf

restriction that an individual choice between two options is independent of any other choices that are available (Cheng & Long, 2007). A limitation of CLM is that it cannot take into account preference heterogeneity. McFadden (1974) suggested that the use of multinomial models 'should be limited to situations where the alternatives can plausibly be assumed to be distinct and weight independently in the eyes of each decision-maker'.

Conditional logit model

CLM was used to compare estimates between weight groups. The utility function for individual i, with j alternatives in scenario s is defined by Equation 5-4:

$$\boldsymbol{U_{ijs}} = \boldsymbol{X'_{ijs}\beta_i} + \boldsymbol{\varepsilon_{ijs}} \qquad (5\text{-}4)$$

where β_i is a vector of coefficients and X'_{ijs} is a vector of explanatory variables. In this model, we assume the error term to be identically and independently distributed (iid).

Test for the IIA assumption

Due to the assumption in the multinomial logit model of IIA, there is concern that it is not an appropriate model for estimating preferences. The IIA assumption implies that an individual's choice between two options is independent of other choices that may be available (Cheng & Long, 2007). Many models appear to fail tests for IIA and often reject the use of CLM for analysing choice data.

To test whether the IIA assumption was violated, a partition test was conducted. In this test, both a restricted model and unrestricted model were estimated using the 'suest'[54] command in Stata, which is a post-estimation command for testing cross-model hypotheses. The command allows for the clustering of standard errors and the model specified to cluster around respondent id to control for intragroup correlation as proposed by Hausman and McFadden (1984). Cheng and Long (2007) concluded that tests for IIA have many limitations and may not be appropriate for assessing the use of MNL models.

Heterogeneity between the different weight groups was tested in Stata by comparing the predicted values for the three BMI weight groups (normal, overweight, obese) and the whole sample. Using the likelihood-ratio (LR) statistic, the null hypothesis that the respondents' preferences are stable across weight groups was tested. The LR test compares the log likelihood

[54] Seemingly unrelated estimation: https://www.stata.com/manuals13/rsuest.pdf

the restricted model (all respondents) with the unrestricted model (three BMI groups) and tests whether this is significant.

A second method was also employed that used the 'suest' command and then tested the null hypothesis that coefficients from the full model (with all weight groups) were equal to the coefficients from the weight group models.

Preference heterogeneity

Allowing for the fact that some individuals prefer particular attributes, random parameter models have been employed to control for variations in the behaviour of (Gu et al., 2013). The mixed logit model (MIXL) allows for unobserved preference (or taste) heterogeneity and violation of the IIA assumption. The mixed logit model builds upon the conditional logit model by specifying one or more variables in the model to be random (Hole, 2013). Equation 5-5 outlines the MIXL model where the utility for individual i associated with choice j in scenario s is:

$$\boldsymbol{U_{ijs}} = \boldsymbol{\beta X'_{ijs}} + \left(\boldsymbol{\eta_i X'_{ijs}} + \boldsymbol{\varepsilon_{ijs}}\right) \tag{5-5}$$

where β_i is a vector of coefficients, X'_{ijs} is a vector of explanatory variables and η_i is a variability term. For the DCE, each MIXL model run was specified for 500 Halton draws. The final two models assumed both a normal distribution and a log distribution. The mixed logit model only permits 20 random covariates when estimated in Stata; therefore, both cost and reward were specified as continuous and non-random. There is no defined method to determine which attributes to vary and what distribution to use; it is recommended that 'a combination of intuition and statistical tests be used (such as the likelihood ratio test) to decide on which coefficients to vary' (Hole, 2013).

Latent class models allow for exploration of unobserved groups in the data. Latent class models (Hole, 2008) assume the distributions of the coefficients are discrete, rather than continuous (Hole, 2013). In the latent class model, preferences vary across classes, rather than within classes. These models were run in Stata using the '*lclogit*' command.

Prior to estimating the latent class model, the number of optimal classes needs to be determined. The procedure to determine the optimal number of classes is to run several models with differing class numbers (e.g., 2–10) (Stata.com; Pacifico & Yoo, 2013). The optimal number of classes is chosen by comparing Akaike's information criterion (AIC), Consistent Akaike's information criterion (CAIC) or Bayesian information criterion (BIC) and choosing the model with the lowest AIC, BIC or CAIC. Based on a study by Nyland et al. (2007), comparing information criterion, the AIC did not appear to be a good indicator as there is no adjustment for sample size and accuracy decreases as sample size increases. The study concluded that the CAIC was an improvement over the AIC; however, BIC was superior overall.

Scale heterogeneity

The conditional logit, mixed logit and latent class models assume that preference heterogeneity is the main reason individuals make different choices. An alternative assumption is that the preference heterogeneity could be described as scale heterogeneity, in which the scale of the error term differs between individuals, implying that choice behaviour is more random for some individuals (Louviere et al., 1999). The generalised multinomial model (GMNL) expands on the mixed logit model by taking into account both within- and between-person variability (Louviere & Lancsar, 2009). Fiebig et al. (2010) found that

> Accounting for scale heterogeneity enables one to account for 'extreme' consumers who exhibit nearly lexicographic preferences, as well as consumers who exhibit very 'random' behaviour. (p. 393)

A GMNL model was employed in Stata using the user-written 'gmnl' command. The model is specified for individual *i* associated with choice *j* in scenario *s* as in equation 5-7:

$$\boldsymbol{U_{ijs}} = (\boldsymbol{\sigma_i \beta} + \boldsymbol{\eta_i})\boldsymbol{X_{ijs}} + \boldsymbol{\varepsilon_{ijs}} \tag{5-6}$$

where X'_{ijs} is a vector of explanatory variables and σ_i is the scale parameter. The scale parameter is assumed to be log-normally distributed with its mean equal to 1 (Hess & Train, 2017). The scale parameter is specified in Stata to be 1 for continuous variables and 0 for all dummy variables. This specifies that the cost variable is scaled and the dummy variables are not scaled. Two models were estimated, a restricted model and an unrestricted model.

Willingness to pay

Since cost is an attribute included in the DCE, it is possible to estimate the monetary value of each attribute – in other words, how much respondents are willing to pay to gain an improvement in one of the other attributes. This marginal willingness to pay (mWTP) for each attribute level is calculated as the negative of the ratio between the coefficient of that attribute and the cost attribute (Grisolia et al., 2013). The attributes in this model (other than cost) were included as factor variables; therefore, the WTP for each level compared to the base case can be calculated. The WTP for each of the attribute levels compared to the base case can be estimated as:

$$\boldsymbol{WTP} = -\frac{\partial \boldsymbol{V_{ij}} / \partial \boldsymbol{x_{ijq}}}{\partial \boldsymbol{V_{ij}} / \partial \boldsymbol{x_{ijc}}} = -\frac{\boldsymbol{\beta_{ijq}}}{\boldsymbol{\beta_{ijc}}} \qquad (5\text{-}7)$$

where x is a vector of attributes and q represents the 22 levels from all attributes (other than cost) and c is the cost attribute. WTP was calculated using the nonlinear combination of estimators command in Stata (*nlcom*)[55] (Stata.com), utilising the estimates from the mixed logit model. This command provides confidence intervals using the delta method. Two different models were run to estimate the mWTP: (1) using just the cost variable as the cost parameter and (2) using the net cost (i.e., the difference between the cost and reward variables).

5.11.4 Sensitivity analyses

Sensitivity analyses were conducted excluding non-traders, those who failed the dominant task set, those who finished the whole survey in under three minutes and 45 seconds and respondents who always chose the same alternative.

Non-traders: Variables were created for respondents who always chose the lowest cost or the largest weight loss. Identifying these non-traders is important, as there is some debate about whether to include these respondents when attempting to determine the marginal rate of substitution between different attributes (Cairns & van der Pol, 2004). A sensitivity analysis was conducted excluding the non-traders, as the respondents may have lexicographic preferences.[56] However, Cairns and van der Pol found that non-trading was mostly due to preference rates outside the levels of attributes displayed. For this reason, it is also important to consider including all non-traders in the analysis.

[55] The 'nlcom' command in Stata calculates 'point estimates, standard errors, test statistics, significance levels and confident intervals for nonlinear combinations of parameter estimates'. This can be employed after any Stata command.

[56] Lexicographic refers to preferences that in which an individual prefers all combinations that contains more of good X to any amount of good Y. Furthermore, if there were two combinations where X was equal, the bundle with more of good Y would be preferred.

Dominant choice task: As described in Section 5.7.1, the ninth (and final) choice set contained a dominant set of options. In this choice set, option 1 included the best overall health outcomes, least cost, highest reward and least time commitment. Those respondents who chose option 2 were excluded and the conditional logit model re-estimated.

Time constraints: In online experiments, there is temptation for respondents to pick choices at random in a timeframe that would not be considered sufficient to evaluate the choice sets appropriately. The industry standard is to remove respondents who take less than one third of the total median time to complete the survey (Personal discussion with Qualtrics – online survey provider). As the median survey completion time was 11 minutes and 12 seconds, respondents were excluded from the sensitivity analysis if they completed the survey in less than three minutes and 45 seconds. The model was re-estimated excluding all those respondents who finished the survey in under three minutes and 45 seconds.

Alternative constant: A common finding in DCEs is that some respondents will always choose the same alternative. In this experiment, the model was run excluding respondents who always chose the left-side alternative (Program 1) or the right-side alternative (Program 2) for all eight choice tasks.

5.12 Survey Results

Table 5.10 summarises how the DCE dataset was constructed. Data from the CHERE pilot, Pilot 1 and Pilot 3 were excluded from the final dataset because of changes made to the choice sets or experimental design. Data from Pilot 2 and the full sample were combined, resulting in a total of 1,598 (101 + 1,497) respondents who completed the full survey. In addition, 50 respondents were included that completed the DCE questions but did not complete the full survey (due to timeout). These respondents were therefore added to the DCE dataset. In total, there were 1,648 respondents in the full DCE dataset (response rate 1648/1898 = 83%). The pilot data was included in the full DCE dataset, as the 9 DCE choice tasks included were identical to the final sample collected and provided data on 103 additional individuals.

Table 5.10 Total responders

	Completers	Non-completers		DCE dataset
		Full DCE data	No DCE data	
Pilot CHERE	10	0	0	
Pilot 1	104	12	1	
Pilot 2	101	2	15	103
Pilot 3	121	2	15	
Full Sample	1497	48	235	1545
Total respondents	**1833**	**64**	**266**	**1648**

5.12.1 Respondent characteristics

The DCE respondents were generally similar to the Australian population (Table 5.11). The age of the respondents was well matched with the Australian population, with only a slightly larger percentage of respondents aged 55–74. The percentage of males and females (52.2% and 47.4% respectively) differed slightly from the Australian population (49.6% and 504% respectively). The respondents differed from the Australian population in terms of educational attainment and labour force participation; a higher percentage of respondents had higher degrees, but a lower number were in full time employment. In terms of birth country, a higher percentage of survey respondents were born in Australia than in the general population.

Table 5.11 Respondent Characteristics

Characteristic	Respondents (N = 1648)	Percentage	Australian Population Percentage
Gender			
Female	782	47.5	50.4
Male	860	52.2	49.6
Other	6	0.4	NR
Age			
18–24	173	10.5	12.3
25–34	347	21.1	19.3
35–44	284	17.2	17.2
45–54	245	14.9	16.8
55–64	298	18.1	14.8
65–74	221	13.4	11.1
75+	80	4.9	8.5
Aboriginal or Torres Strait Islander origin			
Yes	66	4.0	3.4
No	1582	96.0	96.6
Birth country			
Australia	1243	75.4	66.7
New Zealand	38	2.3	2.2
UK	123	7.5	4.5
Other	244	14.8	26.6
Aboriginal or Torres Strait Islander origin			
Yes	66	4	3.4
No	1583	96	96.6
Education			
Year 11 and below	240	14.6	26.0
Year 12	258	15.7	18.7
Certificate (any level)	342	20.8	18.8
Diploma/advanced	243	14.8	10.1
Bachelors or above	565	34.3	26.4
Living situation			
Single, never married	408	24.8	35.0
Married	795	48.2	48.1
Divorced/separated/widowed	203	12.3	16.9
Other	242	14.7	-
Income[a]			
Negative or zero income	20	1.2	0.4
$1 - $19,999	119	7.2	4.3
$20,000–$49,999	384	23.3	27
$50,000–$79,999	301	18.3	15.2
$80,000–$109,999	261	15.8	17.8
$110,000–$149,999	190	11.5	11.1
$150,000–$199,999	90	5.5	8.9
$200,000 +	64	3.9	15.3
Don't know	51	3.1	-
Prefer not to say	168	10.2	-
Work status			
Full time paid work	527	32.0	47.8
Part time paid work	128	7.8	
Self-employed	264	16.0	12.5
Other	729	44.2	39.7

[a] *The ABS data were published as weekly household income, therefore groups may not be exact due to rounding to the nearest pay bracket. Source: Australian Bureau of Statistics, 2017a; Australian Bureau of Statistics, 2016; Australian Bureau of Statistics, 2017c; Australian Bureau of Statistics, 2017b. NR: not reported.*

5.12.2 Health and weight-related characteristics

A summary of the respondents' height and weight characteristics are provided in Table 5.12. Overall, 33.8% of respondents were overweight and 27.6% were obese, as classified by BMI. This is comparable to the Australian population (35.5% overweight and 27.8% obese). The average BMI was identical to the Australian population (27.5). Given the small number of respondents who were underweight, these respondents were included in the normal weight group. In all DCE analyses, respondents were classified as either normal weight, overweight or obese.

Table 5.12 Respondent BMI characteristics

Characteristic	N	Percentage	Mean	Australian population[a]
Respondents	**1648**			
Height			**170.5**	
Females	782	48	164.2	162.2
Males	861	52	176.2	176.1
Weight			**80.3**	
Females	782	48	74.2	71.4
Males	861	52	85.8	86.4
BMI			**27.5**	**27.5**
Females	782	48	27.2	27.2
Males	861	52	27.6	27.8
Weight groups				
Underweight	43	2.6%		1.6%
Normal weight	589	35.7%		35.0%
Overweight	557	33.8%		35.5%
Obese	459	27.6%		27.8%

[a]*Source: ABS, National Health Survey: First Results, 2014-15*

Table 5.13 summarises the health characteristics of the respondents in the survey. Generally, respondents reported their health status to be very good or good. Currently, 14% of Australians smoke, a similar proportion to the survey respondents. More than half of respondents (56.5%) reported the presence of an ongoing medical condition. In 2014–15, approximately 17.5% of Australians reported having a mental or behavioural condition (Australian Bureau of Statistics, 2015), similar to the 18.2% of survey respondents. The sample had a slightly higher percentage of respondents with Type 2 diabetes (8.4%) compared to 4.4% of Australians in 2014–15 (Australian Bureau of Statistics, 2015).

Table 5.13 Respondent health characteristics

Characteristic	Number of respondents	Percentage
Respondents	**1,648**	**100%**
Health status		
Excellent	136	8.3%
Very good	509	30.9%
Good	604	36.6%
Fair	300	18.2%
Poor	100	6.1%
Health conditions		
Arthritis	274	16.6%
Asthma	184	11.2%
Cancer	46	2.8%
Type 1 Diabetes	15	0.9%
Type 2 Diabetes	139	8.4%
COPD	39	2.4%
Chronic pain	203	12.3%
Depression or mood disorders	300	18.2%
Heart disease	68	4.1%
High blood pressure or hypertension	333	20.2%
No ongoing medical conditions	717	43.5%
Other	128	7.8%
Smoking status		
I have never smoked	863	52.3%
I used to smoke but no longer smoke	477	28.9%
I smoke everyday	238	14.4%
I smoke at least weekly (but not daily)	34	2.1%
I smoke less often than weekly	37	2.2%
Alcohol consumption		
I have never drunk alcohol	180	10.9%
I used to drink but no longer drink	225	13.6%
I drink alcohol everyday	150	9.1%
I drink at lease weekly (but not daily)	510	30.9%
Yes, but only rarely	584	35.4%

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Table 5.14 reports the results from the weight-related questions. Interestingly, only 44.2% of respondents considered themselves overweight, despite the fact that 61.4% were overweight or obese based on BMI. Moreover, 56.3% of respondents were currently trying to lose weight. This discrepancy between how individuals perceive their weight versus their actual weight status is well-documented, demonstrating that many obese individuals inaccurately perceive their weight category (Mueller et al., 2014; Johnson et al., 2014). Furthermore, studies have shown that those who inaccurately assess their weight have lower levels of QoL (Park et al., 2017). A sensitivity analysis using perceived weight was conducted to compare this with actual weight classifications.

Table 5.14 Respondent weight characteristics

Characteristic	Number of respondents	Percentage
Respondents	**1,648**	**100**
Weight status		
Acceptable weight	849	51.5
Underweight	72	4.4
Overweight	728	44.2
Weight satisfaction		
Very satisfied	146	8.9
Satisfied	431	26.1
Neither satisfied nor dissatisfied	374	22.7
Dissatisfied	512	31.1
Very dissatisfied	186	11.3
Overweight status		
Used to be overweight/normal weight now	351	21.3
Never been overweight	574	34.8
Currently overweight	724	43.9
Currently trying to lose weight		
No	720	43.7
Yes – diet	233	14.1
Yes – increasing physical exercise	269	16.3
Yes – diet and physical exercise	427	25.9
Dieted in past year		
Never	804	48.8
Once	272	16.5
More than once	402	24.4
Always on a diet	171	10.4
Paid weight-loss program		
Yes	256	15.5
No	1,393	84.5
Moderate activities in a week		
Not at all	208	12.6
Less than once a week	277	16.8
1-2 times a week	457	27.7
3-6 times a week	459	27.8
Everyday	248	15.0
Vigorous activities in a week		
Not at all	758	46.0
Less than once a week	308	18.7
1–2 times a week	327	19.8
3–6 times a week	212	12.9
Everyday	44	2.7

5.12.3 Quality of life results

A total of 1,640 respondents provided EQ-5D-5L data. Out of the total dataset of DCE respondents, eight did not complete the QoL questionnaire. Table 5.15 summarises respondents' QoL by gender, BMI category, health status and medical conditions.

Table 5.15 Respondents' Quality of Life (EQ-5D-5L) summary scores

Characteristic	N	Mean	95% CI
All Respondents	1640	0.751	(0.738, 0.765)
EQ-5D-5L score			
Females	779	0.750	(0.731, 0.769)
Males	855	0.760	(0.738, 0.775)
Other***	6	0.201	(–0.019, (0.420)
BMI groups* **			
Normal weight	630	0.814	(0.794, 0.835)
Overweight	552	0.752	(0.730, 0.775)
Obese	458	0.665	(0.640, 0.690)
General Health			
Excellent	135	0.881	(0.841, 0.921)
Very good	507	0.849	(0.828, 0.870)
Good***	600	0.782	(0.763, 0.801)
Fair***	298	0.610	(0.583, 0.638)
Poor***	100	0.321	(0.275, 0.368)
On-going Medical Conditions* **			
Yes	926	0.667	(0.650, 0.683)
None	714	0.861	(0.842, 0.881)

****All pairwise comparisons were tested and statistically significant at a p-value <0.001*

The average QoL of all respondents was 0.751, with males having slightly lower QoL (0.750) than females (0.760). As expected, the QoL for the normal weight respondents was higher than the overweight and obese respondents. Those respondents who reported having poor health had the lowest QoL, at an average of 0.321. Those respondents who had an ongoing medical condition also had significantly lower QoL.

All groups were tested by pairwise comparisons and males and females did not have statistically significantly different QoL scores. There were no significant differences between the underweight group and the other weight groups, and this group was added to the normal weight group for all summary statistics. All other BMI categories differed significantly in terms of QoL, as did those with medical conditions compared to those without

The lowest QoL score was –0.676. Overall, 2.1% of respondents had negative QoL values. The largest proportion of respondents had full health (27.9%) and almost half of the respondents had values over 0.839. Appendix 19 summarises the percentage of respondents by levels in each of the five domains of the EQ-5D-5L.

A further evaluation of the EQ-5D scores controlling for other demographic characteristics was conducted to see if the effect of BMI on EQ-5D was still significant. After controlling for age, gender, ongoing medical condition, education, income and marital status, the association between BMI and EQ-5D scores remained significant. A pairwise comparison of the adjusted means across all the BMI groups resulted in significant differences across all groups. Due to the unequal group sizes, the Tukey-Kramer method was applied in Stata to test whether the pairs were significantly different. Overall, a one-unit change in BMI resulted in a 0.008 decrement in utility. The resulting adjusted mean EQ-5D scores were as follows:

- Normal weight: 0.798
- Overweight: 0.747
- Obese: 0.693.

5.12.4 Time to complete the survey

The average time taken to complete the survey was approximately 13 minutes. The minimum time was two minutes and the maximum time was two hours 10 minutes. Eighteen respondents (1.1%) completed the survey in less than three minutes. Eighty-five (5.2%) respondents completed the survey in less than five minutes.

5.12.5 Enrolment in intervention

After each of the DCE vignettes, the respondents were asked '*If you were overweight and the program you chose were available, would you 1) enrol in the program, 2) do nothing*'. Overall, 23% (n=371) always chose 'enrol' and 25% (n=414) always chose 'do nothing'. Those who always chose 'do nothing', were more likely to be male, overweight, older, very satisfied with their current weight and not currently trying to lose weight. Table 5.16 displays the characteristics of those who always chose to not enrol in the weight-loss intervention.

Table 5.16 Characteristics of non-enrollers

Characteristic	All respondents N	%	Non-enrollers N	%
Respondents (N)	**1,648**			
Always enrol	371	23%		
Sometimes enrol	863	52%		
Never enrol	414	25%	**414**	
Gender				
Female	782	48%	129	31%
Male	860	52%	284	69%
Other	6	0%	1	0%
BMI Group				
Underweight	43	3%	8	2%
Normal weight	589	36%	132	32%
Overweight	557	34%	160	39%
Obese	268	16%	70	17%
Severely obese	191	12%	44	11%
Age				
18–24	173	11%	18	4%
25–34	347	21%	63	15%
35–44	284	17%	51	12%
45–54	245	15%	75	18%
55–64	298	18%	90	22%
65–74	221	13%	83	20%
75+	80	5%	34	8%
Weight status				
Acceptable weight	849	52%	214	52%
Underweight	72	4%	15	4%
Overweight	728	44%	185	45%
Weight satisfaction				
Very satisfied	146	9%	51	12%
Satisfied	431	26%	110	27%
Neither satisfied nor dissatisfied	374	23%	109	26%
Dissatisfied	512	31%	117	28%
Very dissatisfied	186	11%	27	7%
Overweight status				
Was overweight/normal weight now	351	21%	79	19%
Never been overweight	574	35%	154	37%
Currently overweight	724	44%	181	44%
Currently trying to lose weight				
No	720	44%	242	58%
Yes – diet	233	14%	45	11%
Yes – increasing physical exercise	269	16%	59	14%
Yes – diet and physical exercise	427	26%	68	16%

5.12.6 Perceived weight

An analysis was conducted on self-reported weight status: '*Do you consider yourself to be: 1) acceptable weight, 2) underweight, 3) overweight*', to test whether there was any difference between people who consider themselves normal weight but who are in fact overweight. Table 5.17 summarises the responses of weight perception relative to actual BMI.

Table 5.17 Weight perception responses

	Mean BMI	Percentage of respondents	Percentage who have correctly perceived their weight
Acceptable weight	24.3	51.5	85.9
Underweight	20.5	4.4	50.4
Overweight	32.0	44.1	48.2

Overall, 85.9% of normal weight respondents correctly classified themselves as normal weight, whereas only 48.2% of overweight/obese individuals correctly identified themselves as overweight or obese. Table 5.18 further segments the data by gender and BMI category to explore if perceptions about weight differ between males and females.

Table 5.18 Weight perception by gender

BMI group	Acceptable weight	Underweight	Overweight
All respondents			
Underweight	47.3%	50.4%	2.3%
Normal weight	85.9%	7.8%	6.2%
Overweight	51.4%	0.4%	48.2%
Obese	12.4%	0.7%	86.9%
Severely obese	2.1%	0.0%	97.9%
Male respondents			
Underweight	50.0%	40.0%	10.0%
Normal weight	86.9%	10.4%	2.6%
Overweight	59.7%	0.0%	40.3%
Obese	11.6%	1.4%	87.1%
Severely obese	2.7%	0.0%	97.3%
Female respondents			
Underweight	45.5%	54.5%	0.0%
Normal weight	85.0%	5.6%	9.4%
Overweight	36.2%	0.5%	63.3%
Obese	13.4%	0.0%	86.6%
Severely obese	1.7%	0.0%	98.3%

Respondents classified as overweight based on their BMI were most likely to underestimate their body weight. Only 48.2% of overweight individuals considered themselves to be overweight. Most of the respondents who were obese or severely obese categorised themselves correctly (86.9% and 97.9% respectively). There are some differences in terms of gender. While 60% of overweight males consider that they are an acceptable weight, only 36% of overweight females consider their weight acceptable. The misperception on the part of males may be in part due to the usefulness of BMI as a measurement tool. As muscular men may be misclassified, overweight males who perceive themselves as muscular may not perceive their weight as an issue.

5.13 DCE Results

5.13.1 Conditional logit model (Model 1)

A conditional logit model was run for all respondents as well as for each of the three BMI weight groups. A postestimation command in STATA was run to test the differences in the parameter estimates. The 'suest' command was used and the standard errors adjusted for clustering around observations from the same respondent. Figure 5.5 displays the overall preferences for all respondents.

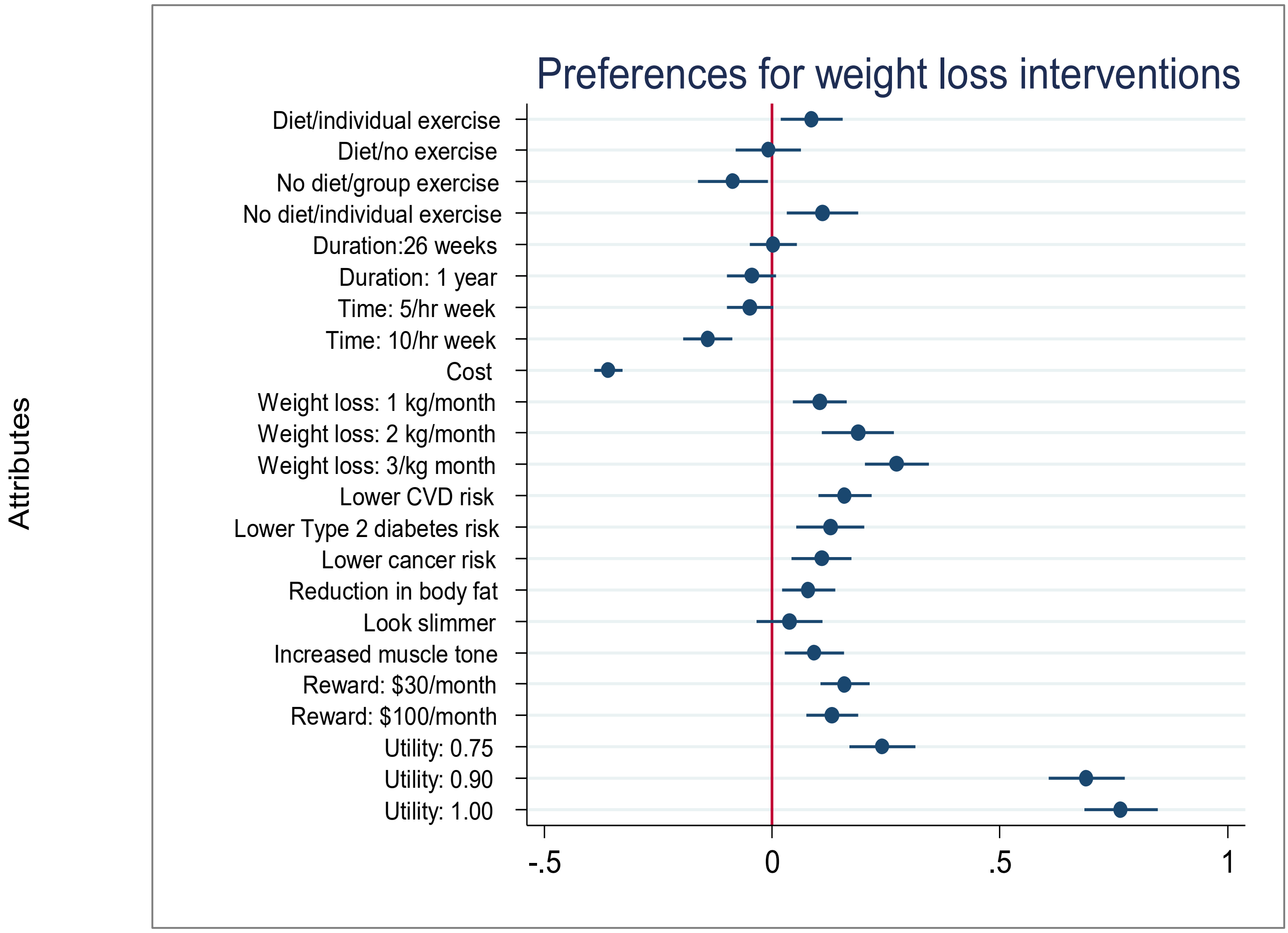

Figure 5.5 Respondent preferences

The conditional logit models demonstrate that respondents had strong preferences for weight-loss programs that provide better health-related QoL, when compared to weight loss, lower disease risk (CVD, diabetes and cancer) and improved body appearance (slimmer and muscle tone). In terms of the characteristics of a weight-loss program, respondents preferred a combined diet and exercise program and lower weekly time commitment, with overall duration non-important. Unsurprisingly, respondents preferred a lower-cost program with higher weight-loss reward. Figure 5.6 displays the preferences of respondents by BMI category.

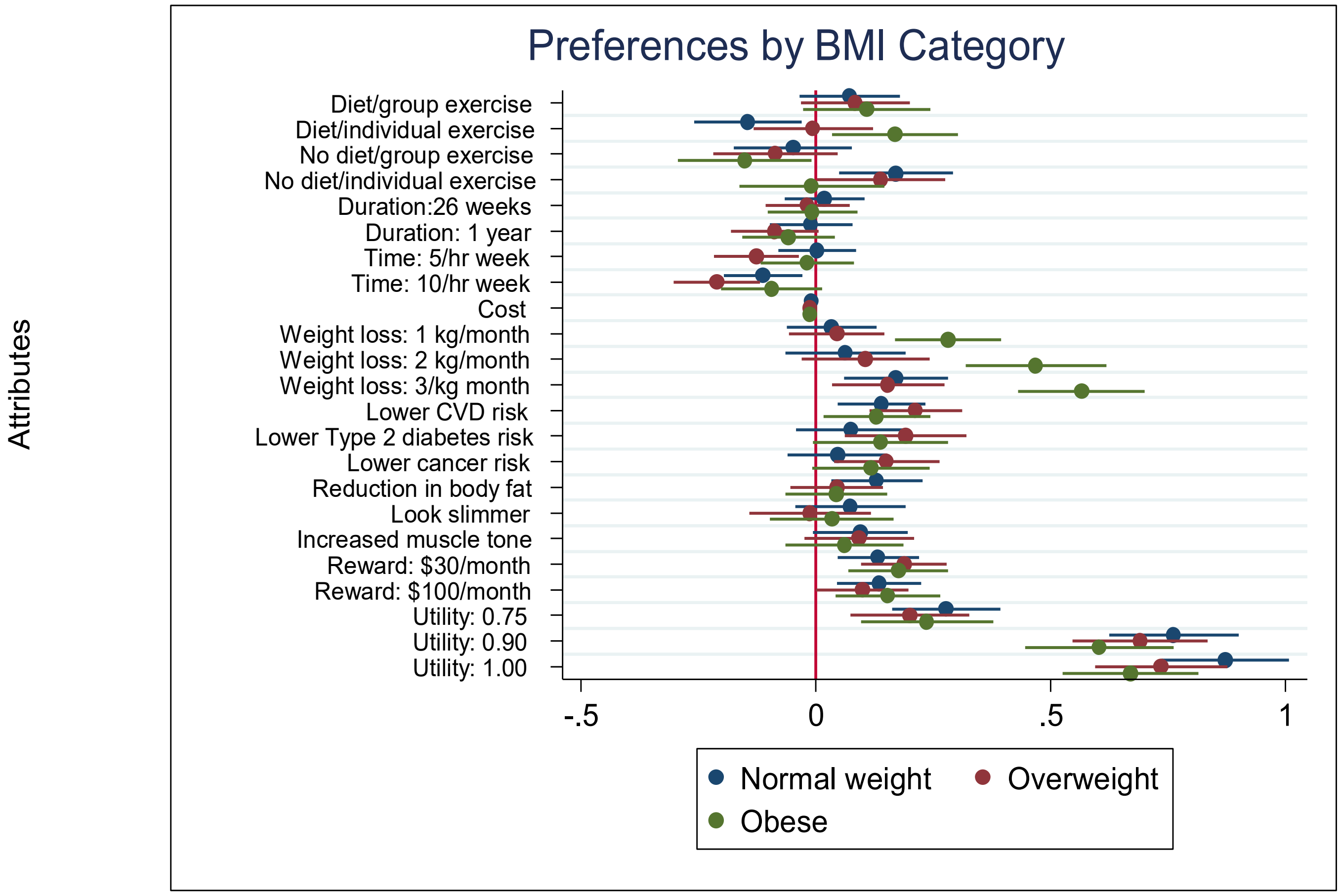

Figure 5.6 Respondent preferences by BMI group

When the respondents were divided into their BMI categories, the largest difference between preferences was for kilograms lost per month. Obese respondents had stronger preferences for weight-loss outcomes than overweight or normal weight individuals. Obese respondents also had a stronger preference for diet and individual exercise programs.

An *a priori* assumption was that respondents would implicitly calculate the net cost of each program by summing the intervention costs and rewards. A model including interactions between costs and rewards was run to take into account this net cost. None of the interactions between cost and reward were significant and, therefore, all the models were run without this interaction term. Table 5.19 summarises the model output for the conditional logit models of all respondents and by BMI category.

Table 5.19 Regression results (conditional logit)

		All respondents (N=1648)		Normal weight (N=632)		Overweight (N=557)		Obese (N=459)	
		Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Characteristics	**Type of program** (ref: Diet/group exercise)								
	Diet/individual exercise	0.091**	0.035	0.072	0.054	0.084	0.059	0.109	0.069
	Diet/no exercise	–0.009	0.037	–0.145*	0.059	–0.005	0.065	0.168*	0.069
	No diet/group exercise	–0.085*	0.039	–0.049	0.064	–0.086	0.068	–0.151*	0.073
	No diet/individual exercise	0.113**	0.040	0.171**	0.062	0.139*	0.070	–0.008	0.079
	Duration of program (ref: 3 months)								
	6 months	–0.001	0.026	0.019	0.043	–0.018	0.046	–0.007	0.049
	1 year	–0.048	0.027	–0.01	0.045	–0.087	0.048	–0.059	0.05
	Time commitment (ref: 2 hr/week)								
	5 hr/week	–0.044	0.026	0.003	0.042	–0.127**	0.046	–0.018	0.051
	10 hr/week	–0.140***	0.027	–0.113**	0.043	–0.211***	0.047	–0.094	0.055
	Cost of program	–0.011***	0.000	–0.010***	0.001	–0.012***	0.001	–0.012***	0.001
Outcomes	**Weight loss** (ref: 0.5 kg/month)								
	1 kg/month	0.103***	0.030	0.033	0.049	0.044	0.052	0.281***	0.058
	2 kg/month	0.186***	0.040	0.064	0.065	0.106	0.070	0.469***	0.077
	3 kg/month	0.273***	0.035	0.170**	0.056	0.154*	0.061	0.566***	0.069
	Disease risk reduction (ref: No reduction)								
	Lower risk of cardiovascular disease	0.161***	0.029	0.139**	0.048	0.213***	0.050	0.130*	0.058
	Lower risk of Type 2 diabetes	0.130***	0.038	0.075	0.060	0.191**	0.066	0.138	0.073
	Lower risk of cancer	0.106**	0.033	0.046	0.054	0.151**	0.057	0.117	0.064
	Appearance (ref: improved skin and hair)								
	Reduction in body fat	0.080**	0.030	0.130**	0.050	0.045	0.050	0.044	0.055
	Look slimmer	0.038	0.037	0.073	0.060	–0.012	0.066	0.034	0.067
	Increased muscle tone	0.094**	0.033	0.095	0.051	0.092	0.060	0.061	0.064
	Weight loss reward (ref: no reward)								
	$30/month	0.161***	0.027	0.133**	0.044	0.188***	0.047	0.176**	0.054
	$100/month	0.132***	0.029	0.135**	0.046	0.099	0.050	0.154**	0.057
QoL	**QoL scenarios** (ref: 0.60)								
	Utility 0.75	0.241***	0.041	0.277***	0.069	0.201***	0.072	0.237**	0.074
	Utility 0.90	0.690***	0.041	0.762***	0.066	0.690***	0.075	0.604***	0.075
	Utility 1.00	0.764***	0.029	0.872***	0.047	0.735***	0.051	0.671***	0.057
	Log likelihood	–8336		–3197		–2797		–2290	
	AIC	16,719		6,441		5,640		4,626	
	BIC	16,907		6,607		5,803		4,784	

**p<0.05, **p< 0.01, ***p<0.001*

Interactions by obesity

A sensitivity analysis was conducted using interactions with being obese, which combines the data in a single model to analyse the difference between normal and obese individuals. Each of the attribute levels was interacted with a dummy variable representing being obese. Table 5.20 presents the CLM model with both main effects and interactions.

Table 5.20 Regression analysis (interactions with obesity)

		CLM			
		Main Effects		**Interactions with Obese**	
		Coefficient	**SD**	**Coefficient**	**SD**
Characteristics	**Type of program** (ref: diet/group exercise)				
	Diet/individual exercise	0.079*	0.040	*0.027*	*0.080*
	Diet/no exercise	–0.078	0.044	*0.247***	*0.081*
	No diet/group exercise	–0.064	0.047	*–0.089*	*0.086*
	No diet/individual exercise	0.159**	0.046	*–0.172*	*0.091*
	Duration of program (ref: 3 months)				
	6 months	0.004	0.031	*–0.007*	*0.058*
	1 year	–0.044	0.033	*–0.010*	*0.060*
	Cost of program				
	$25	–0.354***	0.001	–	–
	$50	–0.684***	0.048	*–0.085*	*0.083*
	$100	–1.061***	0.058	*–0.109*	*0.092*
	Time commitment (ref: 2 hr/week)				
	5 hr/week	–0.059	0.031	*0.035*	*0.060*
	10 hr/week	–0.158***	0.031	*0.061*	*0.060*
Outcomes	**Weight loss** (ref: 0.5 kg/month)				
	1 kg/month	0.038	0.035	*0.245****	*0.068*
	2 kg/month	0.083	0.047	*0.387****	*0.090*
	3 kg/month	0.165***	0.041	*0.401****	*0.081*
	Disease risk reduction (ref: no reduction)				
	Lower risk of cardiovascular disease	0.171***	0.035	*–0.041*	*0.068*
	Lower risk of Type 2 diabetes	0.126**	0.044	*0.011*	*0.086*
	Lower risk of cancer	0.096*	0.039	*0.024*	*0.075*
	Appearance (ref: improved skin and hair)				
	Reduction in body fat	0.088*	0.035	*–0.042*	*0.065*
	Look slimmer	0.035	0.044	*0.001*	*0.081*
	Increased muscle tone	0.097*	0.039	*–0.035*	*0.075*
	Weight loss reward (ref: no reward)				
	$30/month	0.157***	0.032	*0.019*	*0.063*
	$100/month	0.118***	0.034	*0.040*	*0.066*
QoL	**QoL scenarios** (ref: 0.60)				
	Utility 0.75	–0.080*	0.034	*–0.011*	*0.084*
	Utility 0.90	–0.562***	0.049	*–0.122*	*0.096*
	Utility 1.00	–0.807***	0.050	*–0.134*	*0.089*
	Observations				26,368
	Wald Chi				108.35
	Log-likelihood				-8285.12
	AIC				16,668.26
	BIC				17,069.07

The results demonstrate that the weight loss attribute was highly significant for obese respondents, with the size of the coefficients increasing with greater weight loss from the weight-loss program. This finding is intuitive, as it is likely normal weight and overweight individuals are not trying to lose weight and therefore this attribute would not be of importance. The other attribute that was significant for obese respondents was the preference for interventions that had no exercise component and only changes to diet. This differed in direction from the main effects, where this type of program was less preferred than programs that contained an individual exercise component. Tests for heterogeneity in the dataset are presented in Section 5.13.3.

Preference rankings for type of intervention

An additional analysis used post-estimation commands to estimate the pairwise comparisons of the adjusted means of each of the interventions. A Bonferroni correction was specified to adjust the p-values for the simultaneous comparisons. In Table 5.21, each of the interventions is compared to the other interventions and the significance level of the pairwise differences shown. The results illustrate that respondents have strong preferences for individual exercise compared to group exercise. Respondents would rather enrol in a program that required changes to diet and individual exercise versus group exercise with no dietary restrictions. The other significant result was the preference for individual exercise with no diet compared to no exercise and diet. This indicates that individuals prefer to make changes to their physical activity instead of dietary changes.

Table 5.21 Comparison of preferences for weight-loss interventions

	Diet/Group	Diet/ Individual	Diet/No exercise	No diet/ Group	No diet/Individual
Diet/Group	–	0.087	–0.008	–0.086	0.111
Diet/Individual	–	–	–	–0.173***	0.024
Diet/No exercise	–	–	–	–0.078	0.119*
No diet/Group	–	–	–	–	0.197***
No diet/Individual	–	–	–	–	–

**p<0.05, **p< 0.01, ***p<0.001*

The rankings for the weight-loss program components by obese and normal weight respondents reveal stark differences between the two groups (ordered from least preferred to most preferred). Normal weight individuals prefer all weight-loss programs with an exercise program over no exercise program, in contrast to obese respondents whose most preferred weight-loss program involves no exercise. Moreover, it appears that obese respondents prefer weight-loss programs with a diet component over programs with no dietary restrictions (Figure 5.7).

	Normal weight respondents:	Obese respondents:
Least preferred ↓	• Diet/no exercise	• No diet/group exercise
	• No diet/group exercise	• No diet/individual tailored exercise
	• Diet/group exercise	• Diet/group exercise
	• Diet/individual tailored exercise	• Diet/individual tailored exercise
Most preferred	• No diet/individual tailored exercise	• Diet/no exercise

Figure 5.7 Respondents ranking for type of weight-loss program

5.13.2 Sensitivity analysis

Sensitivity analyses were conducted using MNL models to test whether inclusion/exclusion of atypical respondents impacts the overall estimates. Of the 1,652 respondents, 326 always chose the option with the lowest cost. This equates to 20% of respondents being non-traders with respect to cost. Only 27 respondents always chose the highest weight loss (approximately 2% of respondents). Five per cent of respondents always chose the alternative with the better QoL.

The final choice set for each respondent was pre-coded in the survey to reflect a dominant choice, in that 'most' respondents should prefer one alternative over the other alternative (as previously shown in Figure 5.4). In total, 15% of the sample choose the dominant strategy (247 respondents). These people were excluded from the analysis and a sensitivity analysis conducted.

In total, 34 participants (2.06%) completed the survey in under 3.7 minutes. A sensitivity analysis was conducted excluding these participants from the overall sample.

There were 63 respondents (3.8%) who always chose the left-side alternative and 20 respondents (1.2%) who always chose the right-side alternative. A model was run with the choice as a covariate, resulting in the coefficient on the pair variable being significant and a negative coefficient indicating that there was left-side bias by respondents. Respondents have a tendency to choose one program option ('left–right bias').

Table 5.22 presents the results from the four sensitivity analyses conducted. Overall, the results from the sensitivity analysis did not indicate a need to exclude any of these populations from the dataset. All models run in the main analysis were conducted using all DCE respondents.

Table 5.22 Sensitivity Analysis

		All respondents		Non-traders excluded		Dominant excluded		< 3.7 min excluded		Alternative constant	
		N = 1,648		N= 1,322		N = 1,401		N = 1,614		N = 1,565	
		β	SE	β	SE	β	SE	β	SE	β	SE
Characteristics	**Type of program** (ref: diet/group exercise)										
	Diet/individual exercise	0.091**	0.035	0.102**	0.039	0.137***	0.038	0.103**	0.035	0.133***	0.035
	Diet/no exercise	–0.009	0.037	0.005	0.040	0.04	0.042	-0.002	0.037	0.017	0.038
	No diet/group exercise	–0.085*	0.039	–0.069	0.043	–0.066	0.045	-0.083*	0.040	-0.067	0.040
	No diet/individual exercise	0.113**	0.040	0.108*	0.044	0.156***	0.045	0.120**	0.040	0.136***	0.041
	Duration of program (ref: 3 months)										
	6 months	–0.001	0.026	0.025	0.029	–0.011	0.029	0.000	0.027	0.00	0.027
	1 year	–0.048	0.027	–0.034	0.030	–0.06	0.031	-0.044	0.028	-0.051	0.028
	Cost of program (continuous)										
		–0.011***	0.000	–0.006***	0.000	–0.013***	0.001	-0.011***	0.000	-0.011***	0.00
	Time commitment (ref: 2 hr/week)										
	5 hr/week	–0.044	0.026	–0.033	0.029	–0.064*	0.029	-0.042	0.027	-0.049	0.027
	10 hr/week	–0.140***	0.027	–0.145***	0.030	–0.183***	0.030	-0.139***	0.027	-0.147***	0.028
Outcomes	**Weight loss** (ref: 0.5 kg/month)										
	1 kg/month	0.103***	0.030	0.090**	0.033	0.144***	0.033	0.109***	0.030	0.102***	0.031
	2 kg/month	0.186***	0.040	0.184***	0.044	0.252***	0.044	0.199***	0.041	0.202***	0.042
	3 kg/month	0.273***	0.035	0.307***	0.039	0.357***	0.039	0.284***	0.036	0.291***	0.037
	Disease risk reduction (ref: no reduction)										
	Lower risk of cardiovascular disease	0.161***	0.029	0.166***	0.033	0.191***	0.033	0.164***	0.030	0.166***	0.030
	Lower risk of Type 2 diabetes	0.130***	0.038	0.144***	0.041	0.178***	0.042	0.127***	0.038	0.153***	0.039
	Lower risk of cancer	0.106**	0.033	0.115**	0.036	0.162***	0.037	0.112***	0.034	0.130***	0.034
	Appearance (ref: improved skin and hair)										
	Reduction in body fat	0.080**	0.03	0.071*	0.033	0.096**	0.033	0.086**	0.030	0.075*	0.031
	Look slimmer	0.038	0.037	0.034	0.041	0.085*	0.041	0.043	0.037	0.048	0.038
	Increased muscle tone	0.094**	0.033	0.121***	0.036	0.144***	0.037	0.101**	0.034	0.102**	0.034
	Weight loss reward (ref no reward)										
	$30/month	0.161***	0.027	0.145***	0.031	0.202***	0.030	0.159***	0.028	0.157***	0.028
	$100/month	0.132***	0.029	0.117***	0.032	0.182***	0.032	0.131***	0.029	0.136***	0.030
QoL	**QoL scenarios** (ref: 0.60)										
	Utility 0.75	0.241***	0.037	0.256***	0.041	0.290***	0.041	0.248***	0.037	0.246***	0.038
	Utility 0.90	0.690***	0.043	0.731***	0.048	0.795***	0.047	0.704***	0.043	0.697***	0.044
	Utility 1.00	0.764***	0.041	0.823***	0.046	0.903***	0.046	0.786***	0.042	0.783***	0.043
	Log likelihood	–8336.45		–6866.85		–6847.74		–8132.36		–7867.03	

Preferences by weight perception

A conditional logit (clogit) was estimated for each of the weight perception categories to compare preferences for the weight-loss programs. Figure 5.8 displays the preferences for all respondents based on how they classify their body weight.

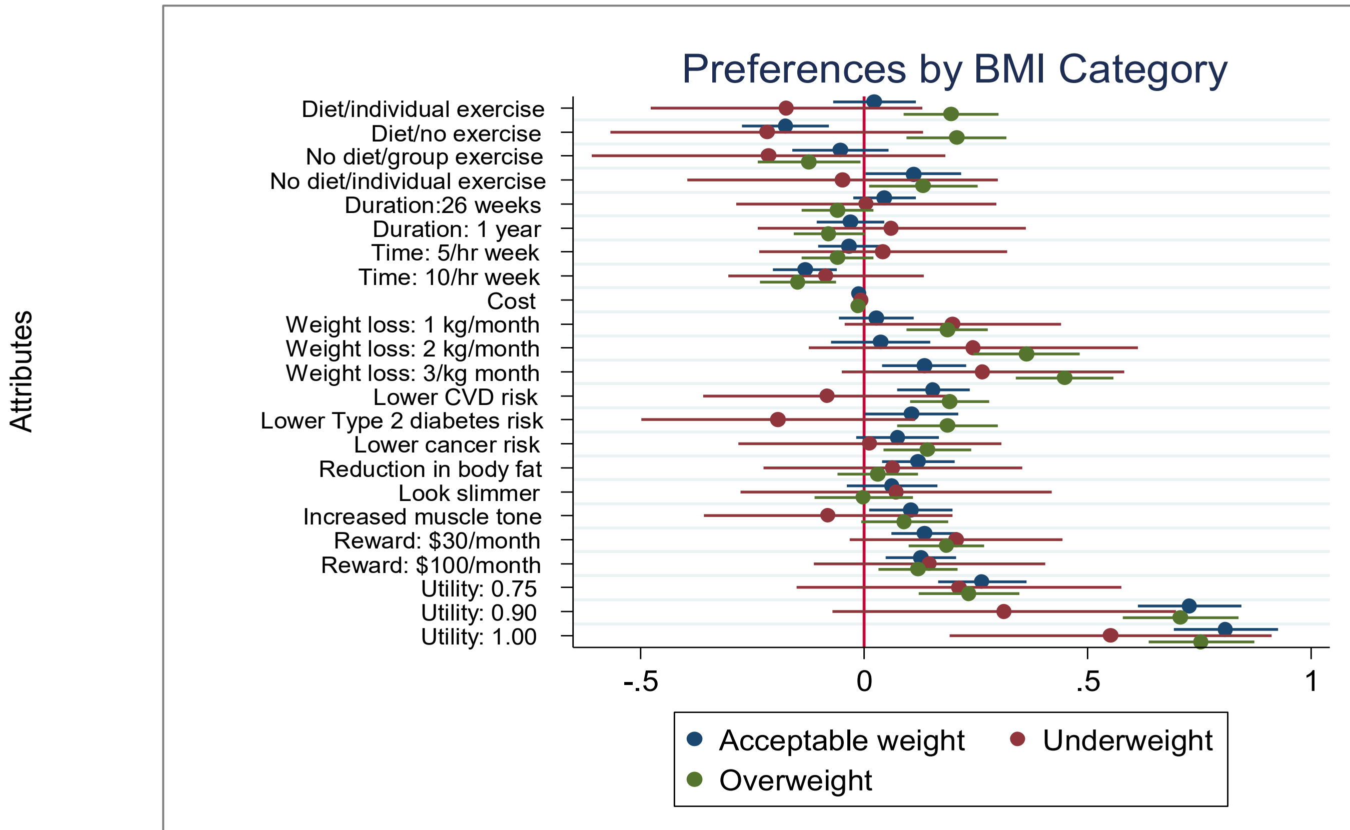

Figure 5.8 Preferences by weight perception

A further analysis was conducted by categorising the respondents into four groups: (1) acceptable/normal/underweight, (2) overweight but consider themselves acceptable weight, (3) overweight and (4) obese. Since, the obese, normal and underweight respondents were more likely to correctly identify their weight category, only the overweight group was segmented into those who correctly identified themselves as overweight and those who thought they had an acceptable weight Figure 5.9.

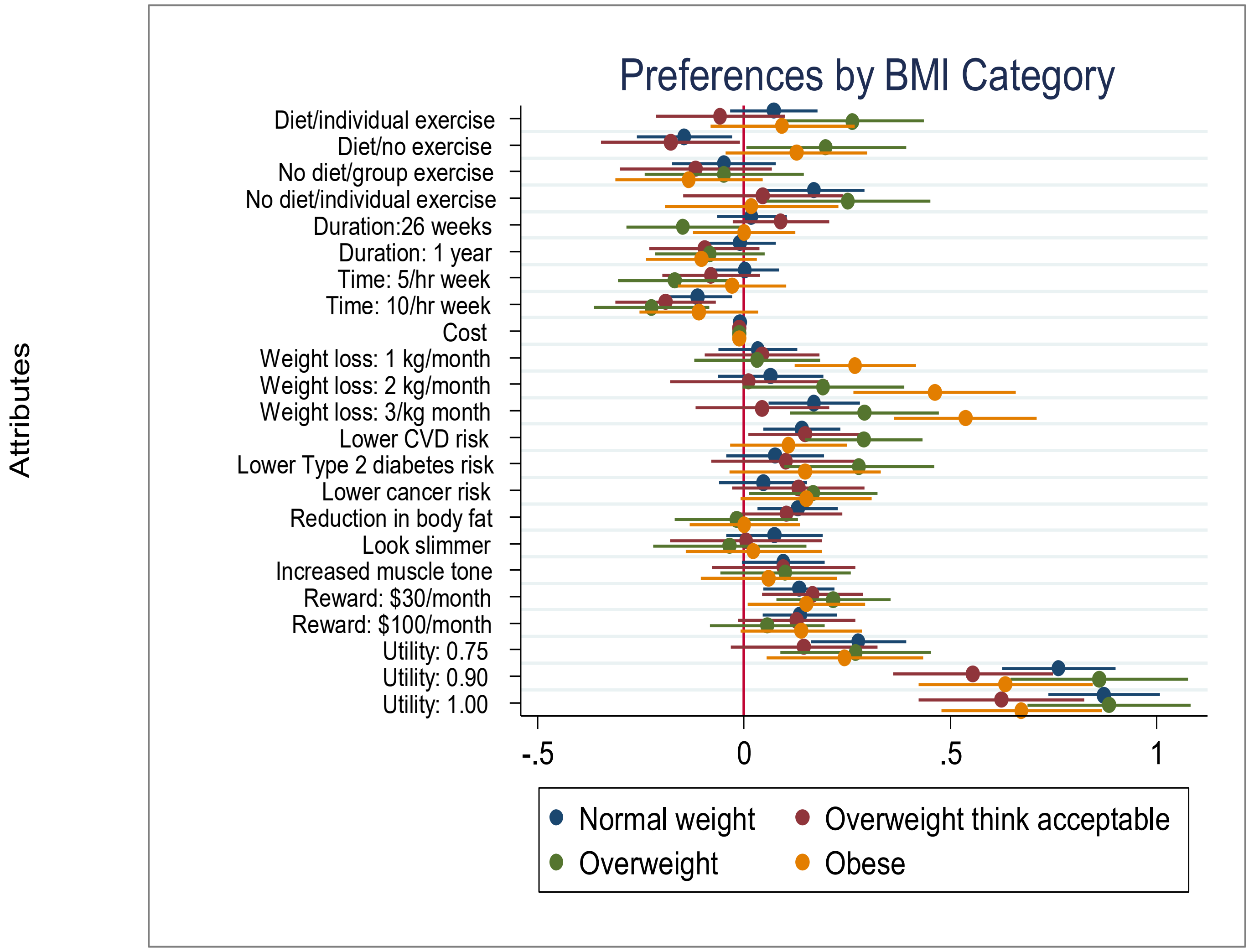

Figure 5.9 Preferences by weight category

The results demonstrate that those respondents who are overweight but consider themselves to be an acceptable weight have preferences more in line with normal weight individuals when considering the QoL aspects of the interventions. Obese respondents had stronger preferences for weight loss than other weight groups.

Non-enrollers

A sensitivity analysis was run comparing those who said they would not enrol in any of the nine weight-loss programs presented to them and those who chose to enrol in one or more of the weight-loss programs. The results are presented in Figure 5.10. Those respondents who would never enrol put less importance on most attributes, with the preferences for higher QoL the only significant attributes. A 'clogit' model with an interaction representing a respondent who 'never enrolled' also resulted in similar preferences.

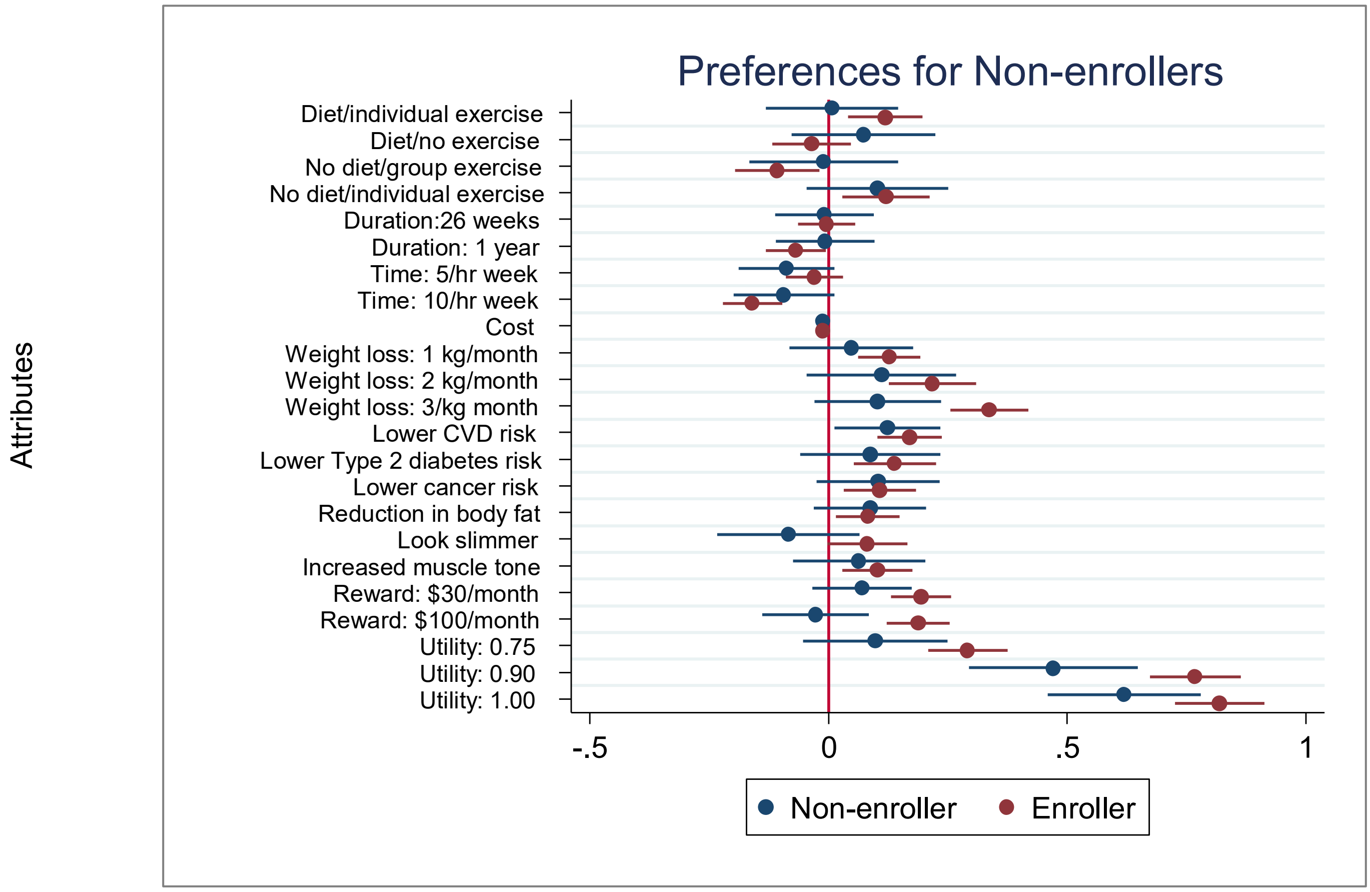

Figure 5.10 Preferences between enrollers and non-enrollers

5.13.3 Heterogeneity

Two methods were employed to test the null hypothesis that respondents' preferences were stable across all weight groups.

Method 1: CLM was estimated for each weight category and the unrestricted scalar calculated. The combined unrestricted log-likelihood (LL) was then calculated. To estimate the restricted model, the '*clogithet*' command in Stata was conducted on the full sample and the log-likelihood calculated. This command fits a heteroskedastic version of McFadden's conditional logit model. (DeShazo & Fermo, 2002; Hensher et al., 1998). The resulting χ^2 using the LL ratio was 103.94 with a p-value < 0.001, thus rejecting the null hypothesis that respondents' preferences are stable across weight groups. This indicates that the three weight groups differ in terms of scale.

Method 2: A poolability test of the three BMI groups was conducted using the post-estimation command 'Seemingly unrelated estimation' (suest) in Stata. The tests results indicate whether the coefficients vary between the BMI groups.

An LR test was conducted to compare the restricted models and the three unrestricted models. The resulting χ^2 value was 104.30 (p-value <0.001), indicating that the null hypothesis could be rejected. This method also supports the finding that there is evidence of scale heterogeneity between the weight groups. Table 5.23 summarises the χ^2 values and significance, comparing each estimated CLM model for weight groups with the restricted model. The 'suest' comparisons indicated that there are preference differences between the overweight and obese respondents.

Table 5.23 Unrestricted and restricted χ^2 estimates

	All	Normal	Overweight	Obese
All	–	0.0098	0.5531	0.0000
Normal	–	–	0.5495	0.0000
Overweight	–	–	–	44.95*
Obese	–	–	–	–

**p<0.05, **p< 0.01, ***p<0.001*

Due to the existence of heterogeneity in the data, additional models were estimated, including a mixed logit, which allows for preference heterogeneity, and the GMNL which allows for both preference and scale heterogeneity. Firstly, the heterogeneity will be explored using latent class modelling.

5.13.4 Latent class model (Model2)

In Stata, a latent class model was run with up to 6 classes to determine what the optimal number of classes for the latent model. Table 5.24 reports the log-likelihood, CAIC, BIC and AIC for statistical comparison of the models.

Table 5.24 Latent class model comparison

Model	Log-likelihood	CAIC	BIC	AIC
2 classes	–8187.881	16770.91	16723.91	16469.76
3 classes	–8057.626	16712.17	16641.17	16257.25
4 classes	–8006.564	16811.82	16716.82	16203.13
5 classes	–7962.56	16925.59	16806.59	16163.12
6 classes	–7933.693	17069.63	16926.63	16153.39

Comparing the CAIC and the BIC for the five models suggest that the latent model should contain three classes. The AIC did not support this result; however, the BIC and the CAIC are commonly used to determine to optimal number of classes, as presented in the '*lclogit*' Stata module (Pacifico & Yoo, 2013) and further discussed in section 5.11.2.

The model with three classes was then used to further explore class membership by running a post-estimation command to determine the posterior probability that the model was accurately predicting taste preferences. The estimated posterior probability was 83%, indicating that model had relatively good predictive power. The results from the latent class model are presented in Table 5.25. The results indicate that respondents across all three classes preferred programs that cost less and improved QoL.

Table 5.25 Latent class model estimates

		Class 1		Class 2		Class 3	
		β	SE	β	SE	β	SE
Characteristics	**Type of program** (ref: diet/group exercise)						
	Diet/individual exercise	0.136**	0.058	0.034	0.158	0.283	0.170
	Diet/no exercise	0.089	0.061	-0.461**	0.207	-0.216	0.243
	No diet/group exercise	–0.048	0.063	-0.124	0.178	-0.359	0.246
	No diet/individual exercise	0.140*	0.064	0.050	0.167	0.179	0.286
	Duration of program (ref: 3 months)						
	6 months	0.022	0.041	-0.042	0.133	-0.300*	0.139
	1 year	–0.029	0.041	-0.156	0.138	-0.302*	0.146
	Cost of program (ref: no cost)						
	$25/month	–0.005***	0.001	-0.011***	0.003	-0.062*	0.012
	Time commitment (ref: 2 hr/week)						
	5 hr/week	–0.030	0.045	0.005	0.112	-0.320**	0.169
	10 hr/week	–0.136**	0.046	-0.196	0.113	-0.332**	0.154
Outcomes	**Weight loss** (ref: 0.5 kg/month)						
	1 kg/month	0.101***	0.047	0.187	0.131	0.273	0.220
	2 kg/month	0.261***	0.065	0.076	0.201	0.295	0.347
	3 kg/month	0.345***	0.053	0.255	0.162	0.325	0.292
	Disease risk reduction (ref: no reduction)						
	Lower risk of cardiovascular disease	0.183*	0.046	0.266*	0.125	0.202	0.170
	Lower risk of Type 2 diabetes	0.149*	0.060	0.287	0.183	0.206	0.214
	Lower risk of cancer	0.126*	0.051	0.130	0.158	0.133	0.207
	Appearance (ref: improved skin and hair)						
	Reduction in body fat	0.097*	0.045	0.057	0.131	0.047	0.139
	Look slimmer	0.073	0.058	-0.072	0.168	0.199	0.182
	Increased muscle tone	0.114*	0.050	0.155	0.160	-0.093	0.195
	Weight loss reward (ref: no reward)						
	$30/month	0.221***	0.042	-0.037	0.143	0.259	0.149
	$100/month	0.175***	0.044	0.033	0.115	0.261*	0.165
QoL	**QoL scenarios** (ref: 0.60)						
	Utility 0.75	0.081	0.049	1.229	0.174	0.302	0.196
	Utility 0.90	0.253***	0.097	3.271***	0.565	0.677*	0.308
	Utility 1.00	0.248***	0.123	3.941***	0.705	0.600	0.219
	Average Class Share	0.58		0.23		0.19	
	LL	–7986.7					
	CAIC	17,209					
	AIC	17,602					
	BIC	16,267					

**p<0.05, **p< 0.01, ***p<0.001*

Respondents in class 2 had significantly stronger preferences for programs with QoL improvements. The preferences from class 1 (with the largest class share), demonstrated similar preferences to the overall results from the clogit, with preferences for weight-loss programs that are of lower cost, reduced duration, greater weight loss, lower risk of associated diseases, offer a reward for losing weight and improve QoL. A preference towards programs with individual exercise programs was also observed.

These results indicate that preferences vary across but not within classes. The characteristics of these unobserved groups were explored using post-estimation commands. Class 1 membership was more likely to comprise males with lower incomes who were overweight and in poorer health. Class 3 membership included more young females with full-time employment compared to class 2 membership, which contained more married people in better health in the normal weight category. The class membership demographics are presented in Appendix 20.

5.13.5 Mixed Logit (Model 3)

A MIXL was estimated to account for preference heterogeneity in the data by allowing one or more of the parameters in the model to be randomly distributed. The first model specified all attributes, other than cost and rewards, as random and was run with normally distributed coefficients. The second model included continuous variables for duration, cost, time commitment and weight loss reward, where all attributes were considered random and modelled as lognormal distributed coefficients. In the second model, prior starting values were not specified and the Stata default was employed. The results from the MIXL are presented in Table 5.26.

The results from the MIXL models are similar to those from the CML and latent class models, with improvements in QoL most preferred. The coefficient on the cost variable varied significantly between the two models. When cost was specified as random with a lognormal distribution, the coefficient was highly significant with an estimate of –4.828, becoming the most important attribute after QoL. It appears that respondents want a weight-loss program that is low cost, improves QoL, does not require a large time commitment, results in significant weight loss and rewards weight loss, reduces disease risk and includes an individual exercise component.

Table 5.26 MIXL Regression results

		MIXL (normal)		MIXL (log)	
		Coefficient	**SD**	**Coefficient**	**SD**
Characteristics	**Type of program** (ref: diet/group exercise)				
	Diet/individual exercise	0.109**	0.455***	0.135**	–0.502***
	Diet/no exercise	–0.026	–0.692***	–0.030	–0.775***
	No diet/group exercise	–0.116*	0.479**	–0.119*	–0.561***
	No diet/individual exercise	0.143**	0.364***	0.165**	–0.343
	Duration of program (ref: 3 months)				
	6 months	0.001	0.012		
	1 year	–0.057	0.311***	–0.002^	–0.012***^
	Cost of program				
	Continuous	–0.013***	–	–4.828***^	1.654^
	Time commitment (ref: 2 hr/week)				
	5 hr/week	–0.061	0.020		
	10 hr/week	–0.167***	0.297***	–0.025***^	0.054***^
Outcomes	**Weight loss** (ref: 0.5 kg/month)				
	1 kg/month	0.121**	–0.066		
	2 kg/month	0.229***	0.281		
	3 kg/month	0.341***	0.493***	0.166***^	0.335***^
	Disease risk reduction (ref: no reduction)				
	Lower risk of cardiovascular disease	0.213***	0.366***	0.253***	0.423***
	Lower risk of Type 2 diabetes	0.176***	0.282	0.253***	–0.279
	Lower risk of cancer	0.128**	0.135	0.174***	0.139
	Appearance (ref: improved skin and hair)				
	Reduction in body fat	0.105**	0.310**	0.122**	0.324**
	Look slimmer	0.045	0.195	0.069	0.257
	Increased muscle tone	0.109**	0.412***	0.132**	–0.343*
	Weight loss reward (ref: no reward)				
	$30/month	0.206***	–		
	$100/month	0.159***	–	0.002***^	–0.007***^
QoL	**QoL scenarios** (ref: 0.60)				
	Utility 0.75	0.295***	–0.206	0.355***	–0.219***
	Utility 0.90	0.845***	0.118	0.974***	–0.040***
	Utility 1.00	0.946***	0.673***	1.108***	0.734***
	Observations	26,368		26,368	
	Wald Chi	137.7		451.16	
	Log-likelihood	–8336.45		–8347.05	
	AIC	16,621.19		16,730.10	
	BIC	16,973.92		16,877.34	

**p<0.05, **p< 0.01, ***p<0.001, ^indicates continuous variables*

5.13.6 Generalised multinomial logit model (Model 4)

The final analysis conducted was a GMNL model to incorporate both taste and scale heterogeneity (Fiebig, 2010). Two models were estimated in which the scale parameter specified which variables were random. In the models, the cost variable was considered non-random and all other variables were specified as being random. The first model was estimated using uncorrelated random coefficients and the second using correlated random coefficients. Table 5.27 displays the results of the GMNL models.

Table 5.27 GMNL Regression Results

		GMNL (uncorrelated)			**GMNL (correlated)**	
		Coefficient	**se**	**SD**	**Coefficient**	**se**
Characteristics	**Type of program** (ref: diet/group exercise)					
	Diet/individual exercise	0.115**	(0.042)	–0.286*	0.191**	(0.057)
	Diet/no exercise	–0.027	(0.047)	0.688***	–0.058	(0.059)
	No diet/group exercise	–0.095*	(0.048)	0.285	–0.111	(0.065)
	No diet/individual exercise	0.153**	(0.047)	–0.096	0.215**	(0.066)
	Duration of program	–0.002	(0.001)	0.009***	–0.004**	(0.001)
	Cost of program	–0.021***	(0.002)	–	–0.031***	(0.003)
	Time commitment	–0.021***	(0.005)	–0.047***	–0.031***	(0.007)
Outcomes						
	Weight loss	0.128	(0.022)	–0.307***	0.191***	(0.028)
	Disease risk reduction (ref: no reduction)					
	Lower risk of cardiovascular disease	0.222***	(0.037)	–0.079	0.272***	(0.051)
	Lower risk of Type 2 diabetes	0.208***	(0.048)	0.280*	0.254***	(0.064)
	Lower risk of cancer	0.162***	(0.042)	0.007	0.187**	(0.056)
	Appearance (ref: improved skin and hair)					
	Reduction in body fat	0.105**	(0.037)	0.197*	0.126**	(0.048)
	Look slimmer	0.059	(0.047)	–0.057	0.074	(0.068)
	Increased muscle tone	0.111**	(0.042)	–0.318**	0.167**	(0.057)
	Weight loss reward	0.002***	(0.000)	0.006***	0.003***	(0.001)
QoL	**QoL scenarios** (ref: 0.60)					
	Utility 0.75	0.327***	(0.046)	0.220	0.444***	(0.061)
	Utility 0.90	0.894***	(0.050)	–0.037	1.257***	(0.081)
	Utility 1.00	1.003***	(0.049)	0.633***	1.397***	(0.082)
	Observations			26,368		26,368
	Wald Chi			589.96		402.09
	Log-likelihood			–8164.72		–7976.78
	AIC			16406.4		16299.55
	BIC			16706.1		17714.68

**p*<0.05, ***p*< 0.01, ****p*<0.001

These results are similar to the MIXL models, in that the most important attribute was QoL and respondents preferred interventions with an individual exercise component. The tau statistics from both the uncorrelated and correlated models were significant at $p<0.001$ (1.518 and 1.696), which indicates that there was scale heterogeneity present in the dataset. The results also demonstrate a better model fit (based on the log-likelihood and the AIC) when the random variables are specified as being correlated.

5.13.7 Overall results and willingness to pay (Model 5)

Based on the comparison of the goodness of fit for the models estimated, it was decided to use a MIXL to estimate the WTP estimates. Table 5.28 summaries the fit criteria for all of the models estimated.

Table 5.28 Model comparison

Model	Log-likelihood	CAIC	AIC	BIC
C-logit	–8336	–	16907	16719
Latent class	–8058	16712	16641	16257
MIXL – normal	–8207	–	16730	16476
MIXL – log	–8065	–	16457	16195
GMNL – uncorrelated	–8165	–	16406	16706
GMNL – correlated	–7977	–	16230	17714

Two mWTP models were estimated; the first included the cost of the program used, the second used the net cost for respondent, which accounts for any rewards available. Table 5.29 describes the value that respondents placed on each attribute relative to the reference group. The MIXL model was considered the best fit based on both the log-likelihood and the BIC. Only the GMNL had better fit than the MIXL according to the AIC.

The results from the WTP estimates demonstrated that respondents placed the highest value on gains in QoL, with respondents willing to pay $71.61 per month for full health, $63.98 per month for a QoL of 0.90 and $22.35 per month for a QoL of 0.75, over the base case QoL of 0.60. The next most important attribute for respondents in terms of willingness to pay was $25.84 per month for a three-kilogram weight loss per month and $17.36 per month for a two-kilogram weight loss. Conversely, respondents would need to be compensated to engage in a weight-loss program with a time commitment of 10 hours a week. Respondents were also more willing to pay for programs that included an individual exercise program and no dietary changes.

5.14 Discussion

The primary aim of this chapter was to ascertain preferences for weight-loss interventions and to determine whether preferences differed between weight group classifications. Respondents had strong preferences for higher QoL and lower costs. Interestingly, normal weight, overweight and obese individuals had similar preferences across attributes, except for weight loss, with obese individuals having significantly stronger preferences for greater weight loss. The initial hypothesis was that normal weight, overweight and obese individuals would have distinct preferences for different weight-loss program characteristics. In terms of the type of weight-loss program, respondents preferred individually tailored programs over group exercise programs; however, this could be costly if targeting a large population.

Table 5.29 WTP estimates

Attributes	mWTP – cost only	(SE)	mWTP – net cost	(SE)
Program Characteristics				
Type of program (ref: diet/group exercise)				
Diet/individual exercise	$8.21**	(3.15)	$11.93	(5.18)
Diet/no exercise	–$1.96	(3.37)	–$4.95	(5.62)
No diet/group exercise	–$8.75*	(3.61)	–$15.85	(6.14)
No diet/individual exercise	$10.81**	(3.53)	$13.90	(6.01)
Duration of program (reference group: 3 months)				
6 months	$0.07	(2.41)	–$4.93	(4.13)
1 year	–$4.30	(2.47)	–$11.90	(4.12)
Time commitment (reference group: 2 hr/week)				
5 hr/week	–$4.61	(2.40)	–$1.76	(3.87)
10 hr/week	–$12.66***	(2.50)	–$17.12	(4.10)
Program Outcomes				
Weight loss (reference group: 0.5 kg/month)				
1 kg/month	$9.19**	(2.67)	$5.72	(4.53)
2 kg/month	$17.36***	(3.55)	$8.97	(5.59)
5 kg/month	$25.84***	(3.28)	$23.79	(5.18)
Disease risk reduction (reference group: no reduction)				
Lower risk of cardiovascular disease	$16.16***	(2.80)	$18.58	(4.36)
Lower risk of Type 2 diabetes	$13.29***	(3.52)	$0.74	(5.94)
Lower risk of cancer	$9.71**	(3.03)	$6.53	(4.98)
Appearance (reference group: improved skin and hair)				
Reduction in body fat	$7.96**	(2.74)	$8.79	(4.41)
Look slimmer	$3.44	(3.49)	$1.66	(5.69)
Increased muscle tone	$8.22**	(3.10)	$3.05	(5.04)
Weight loss reward (reference group: no reward)				
$30/month	$15.60***	(2.45)	–	
$100/month	$12.03***	(2.45)	–	
Quality of life (after the program)				
QoL scenarios (reference case: 0.60)				
Utility 0.75	$22.35***	(3.39)	$19.95	(5.66)
Utility 0.90	$63.98***	(4.06)	$72.38	(7.08)
Utility 1.00	$71.61***	(4.04)	$85.90	(6.46)
Constant				

**p<0.05, **p< 0.01, ***p<0.001*

The results were as expected in terms of costs, where individuals had strong preferences for lower-cost interventions. However, contrary to expectations, the interaction between costs and rewards was not significant. While the *a priori* expectation was that people would calculate the net cost between the cost of the program and the reward offered before deciding between the interventions, these results indicate that respondents considered each attribute individually. This may be because the reward was predicated on losing weight each month, and therefore may have been discounted by some individuals.

Another issue is the fact that preferences for weight loss are misaligned to the data concerning the effectiveness of interventions to reduce weight. As discussed in Chapter 2, a recent meta-analysis demonstrated that interventions including a combination of diet and physical activity may be more effective than diet only. Based on the results of the DCE, individuals preferred weight-loss programs that required changes to physical activity but not diet. This indicates a misalignment between what randomised trials show to be effective and what people prefer to do. This result was consistent with the literature, which demonstrated that individuals preferred changes to physical activity or diet (Grisolia et al., 2013; Ryan et al., 2015) and reluctance to change current lifestyle (Doyle et al., 2012). However, once the obese individuals were analysed separately, a different trend emerged, in which the intervention with no exercise was the most preferred. This contrasts with the normal weight individuals who most preferred the weight-loss program with no dietary requirement and individual exercise. This lends support to designing weight-loss programs for the preferences of the target population as opposed to preferences derived from the general population. The majority of respondents (72%) stated in the feedback questions that they would prefer a weight-loss program that combined diet and exercise.

Another issue in designing interventions is that some individuals are not willing to partake in a weight-loss intervention. In this study, 25% always chose to not enrol. These respondents were more likely to be male, overweight, older and satisfied with their current weight. For these individuals, even larger incentives may be required to convince them adopt healthier lifestyles. Ryan et al. (2014) also reported that one quarter of respondents always chose their current lifestyle over the other intervention options available. A key finding is that paying people to participate in exercise and diet weight-loss programs could increase the uptake of programs. Other studies have demonstrated that men require more compensation than women, so incentives may be a solution to motivate this group. Cawley (2015) proposed that a research priority is to determine what types of incentives (e.g., premiums, co-payments or cash) will motivate individuals to reach a healthy weight. Another issue is determining whether a premium discount or a penalty would be a better motivator. For example, Pomberger et al. (2012) found that grocery vouchers for 'healthy groceries' were preferred to cash incentives.

One issue when including cost in experiments is that people inherently associate higher costs with better quality. In terms of weight-loss programs, individuals may assume a higher cost lifestyle program will be more effective. In DCEs, there is less of a tendency to make this association given that quality and efficacy attributes are presented separately. In this study, effectiveness was determined using weight loss as an attribute, which is also a primary outcome for many weight-loss intervention trials. Another issue with the use of DCEs is that they rely on hypothetical situations and may not fully represent the overall clinical, financial or emotional impact compared to real-world health care decisions (Johnson et al., 2011). Furthermore, the results do not take into account changes to preferences after participation in an intervention. Owen et al. (2009) showed that preferences for lifestyle interventions changed after the conclusion of an intervention. On the other hand, the advantage of DCEs is that they allow policy makers to analyse a new strategy before implementation (Owen et al., 2010).

The inclusion of QoL as an attribute was a novel approach to the DCE. Previous DCEs have only used proxy measures that impact on QoL (such as health gains, appearance or disease risk). The results demonstrated that respondents were motivated by improvements in QoL, as weight-loss programs with the highest QoL improvements were preferred in the DCE. In reality, however, weight loss may not be associated with these large increases in QoL, which may explain why losing weight via a weight-loss program is still difficult since the gains (in terms of QoL) may not compensate the inconveniences (in terms of lifestyle changes and time constraints).

5.14.1 Strengths, limitations and further research

A limitation of all DCEs is that preferences are stated rather than revealed. In the real world, individuals on a weight-loss intervention may not be able to control their lifestyle behaviour as they say they would. Another limitation is the use of an online panel and the generalisability of the responses to that of the general Australian population. The sample of respondents surveyed by Pureprofile tend to be of higher socioeconomic standing and younger; however, the sample was well-matched in terms of weight, which was the most important aspect for this analysis.

The BMI reported in the survey was based on self-reported height and weight, which may have resulted in some respondents being misclassified. As previously discussed, people tend to overstate their height and understate their weight. It is possible that those who do not accurately report their height or weight may bias the results.

The WTP estimates demonstrated that respondents highly valued better QoL. In a real-world setting, what individuals are willing to pay may differ from these estimates. It has been observed that there are discrepancies between what people say they will pay and what they actually pay (Blumenschein et al., 2001). All models resulted in QoL being the most important attribute. It is possible that the way the experiment was presented influenced this result. The display in the experiment had QoL as a separate section and it appeared as four separate attributes. It has been previously demonstrated that the format of DCEs can influence the choices respondents make (Veldwijk et al., 2013).

A strength of the study was that respondents found the survey easy to complete. The majority of the comments were positive, and many respondents indicated that they enjoyed completing the survey. Overall, 82.7% of respondents found the survey easy to understand. This may have positively influenced respondents resulting in more honest answers. The design of the DCE also forced respondents to make a choice between Program 1 and 2 but offered an opt-out option after the questions. This provided additional information compared to a DCE with an opt-out option included as an alternative in the initial choice set.

5.14.2 Conclusion

This DCE was novel in that it compared preferences based on weight categories. Previous studies have also collected BMI information but only compared WTP between the different weight groups (Ryan et al., 2015). The findings from the DCE demonstrate that individuals, regardless of weight status, have strong preferences for weight-loss interventions that improve overall QoL at a lower cost. Many weight-loss programs focus on improvements in weight or other disease risk indicators. These finding indicate that in designing interventions, more attention needs to be paid to improving QoL outcomes. The challenge remains for policy-makers to encourage individuals to change their behaviour and adopt healthier lifestyles.

6 OBESITY AND THE RATE OF TIME PREFERENCES

There is growing evidence that technology changes, leading to lower food prices, increased restaurant density and reduction in the amount of daily physical activity, can partly explain the rise in obesity. However, it is difficult to explain why these changes in economic incentives have affected some individuals more profoundly than others (Courtemanche et al., 2015a). It has been hypothesised that increases in the rate of time preferences may also contribute to the obesity problem, especially if obese individuals discount future benefits differently and therefore have altered responses to incentives (Lakdawalla & Philipson, 2009). If this is the case, the *a priori* expectation is that obese individuals will have more present-bias preferences compared to normal weight individuals, which may provide evidence to explain why changing economic conditions have only affected certain people. This chapter will investigate the role time preferences may play in understanding obesity.

6.1 What are time preferences?

As individuals, we continually make choices between consuming a good immediately or waiting to consume this good. When the choice is to wait for the good, it is because we are waiting for a larger reward (Lawless et al., 2013). An example is buying a car today versus putting that money away for retirement savings (Hardisty et al., 2013). These trade-offs between costs and benefits that occur at different points in time can impact on our health, wealth and overall well-being (Frederick et al., 2002). Individuals with low rates of time preferences tend to be patient, to have self-control and to not discount the future; on the other hand, individuals with high rates of time preference tend to be more present-focused and heavily discount the future (Zhang & Rashad, 2008). It has been theorised that individuals with a high rate of time preferences have a lower demand for future benefits and are less likely to invest in health (Komlos et al., 2004). The concept of time preferences is not new, with the theory discussed by many classical economists, including Adam Smith who wrote:

> The pleasure which we are to enjoy ten years hence, interests us so little in comparison with that which we may enjoy to-day, the passion which the first excites, is naturally so weak in comparison with that violent emotion which the second is apt to give occasion to, that the one could

> never be any balance to the other, unless it was supported by the sense of propriety. (Smith, 1981 [1759], p. 273)

There is evidence to support this theory, that the enjoyment of pleasures today activates emotional regions of the brain that delayed outcomes do not (McClure et al., 2004). The concept of temporal discounting, in which individuals choose an immediate benefit at the cost of forgoing a later benefit, was introduced by Samuelson in his discounting utility (DU) model (Samuelson, 1937). The DU model assumes an individual's time preferences can be captured by a single 'discount rate' that reduces the value of utility in the future (Dodd, 2014; Frederick et al., 2002). The DU model assumes this discount rate is constant over time; for example, the model assumes that if someone prefers \$1 today over \$2 tomorrow, they will also prefer \$1 in 100 days to \$2 in 101 days. The DU model is represented by an individual making choices on a consumption stream over (t) periods. The intertemporal utility function (U) over time (t) can be defined by the following equation:

$$\boldsymbol{U^t(c_t, \ldots, c_t) = \sum_{k=0}^{T-t} D(k)u(c_{t+k})}, \tag{6-1}$$

where $D(k) = \left(\frac{1}{1+p}\right)^k$ is the discount function and p represents the rate of time preference (Frederick et al., 2002). The DU model assumption is that if an individual prefers *X* to *Y*, this individual will prefer *X* to *Y*, regardless of the time period; under this condition, the individual's time preference is characterised by a single discount rate, in other words, a 'time-consistent' rate.

In terms of health, people choose to engage in unhealthy behaviours today because the costs (poor health) are in the future. These choices represent intertemporal trade-offs, which is expressed in terms of a discount rate (Cohen et al., 2016). The concept that time preferences and health choices representing an individual's impatience was an expansion of the human capital model popularised by Gary Becker (1964). Michael Grossman's theory of the demand for health (Grossman, 1972) postulates that people make investments in their health; hence those with lower discount rates would be less likely to engage in unhealthy behaviours that offer immediate gratification (Brown & Biosca, 2016). Previous research has found that preferences for monetary benefits are not consistent with health benefits (Chapman, 2002), with people discounting health outcomes at a higher rate than monetary outcomes (Lazaro, 2002; Lazaro et al., 2002).

6.1.1 Time preference elicitation

The most commonly used method for estimating time preferences is 'Money Earlier or Later (MEL) experiments, where participants are asked to choose between \$X today or \$Y in the future (Cohen et al., 2016). These types of tasks typically ask questions that vary both the time and amount of money (Adams and Nettle, 2009), such as:

1) Would you prefer to receive \$500 today or \$1,000 in five years from today?

2) Would you prefer to receive \$750 today or \$1,000 in two years from today?

These delay discounting (DD) tasks are a behaviour method that elicits individuals' indifference points between a value rewarded now versus a greater value in the future (Hendrickson & Rasmussen, 2013). DD can be classified as an index of self-control and willpower (Basile & Toplak, 2015). Another approach used to determine discount rates is probability discounting (PD), in which respondents are required to choose between a small amount now or a larger amount later (but with variable probability of occurring).

As individuals, we are faced with choices of consuming goods now or waiting to consume goods at a future point in time. Usually individuals will require a greater payoff in the future to wait. The marginal rate of time preference measures 'the rate at which a person is willing to trade current pleasure for future pleasure' (Komlos et al., 2004). The discount rate is measured using the following formula, where σ is an individual's time preference:

$$\boldsymbol{DR} = \frac{\mathbf{1}}{(\mathbf{1} + \boldsymbol{\sigma})} \tag{6-2}$$

The time preference variable (σ) can range between 0 and infinity. If an individual prefers current utility to future utility, the rate of time preferences is higher and the discount rate lower. The two extremes of time preferences are individuals who:

1) Value the present and the future equally: $\sigma = 0$, therefore *DR = 1*

2) Place no value on future utility: $\sigma = \infty$, therefore *DR ~ 0.*

This intertemporal discount rate assumes that σ is constant over time and uniform across different types of consumption (Zhang & Rashad, 2008). Empirical research shows, however, that individuals' preferences are inconsistent, and the concept of constant time preferences does not hold (Laibson, 1997). Psychologists and behavioural economists have suggested that the preference for present consumption may reflect hyperbolic or quasi-hyperbolic discounting (Benhabib et al., 2004), whereby the discount rate falls as the time horizon increases (σ is smaller over long time periods compared to short time periods). Other departures from the DU model are patterns whereby individuals discount gains more than losses (sign effect), and discount smaller amounts more than larger amounts (magnitude effect) (Frederick et al., 2002). There exists a large literature exploring which methods are best for measuring time preferences and growing research on temporal choices has focused on comparing exponential versus hyperbolic discounting models (Hardisty et al., 2013).The discount rate *D*(*y, t*), where *t* is the time delay between receiving the dollar amount (*y*), can be represented by the following functions (Benhabib et al., 2004):

1) D(y,t) represents exponential discounting if:

$$\boldsymbol{D(y,t) = exp\,\{-rt\},\;\; r > 0} \tag{6-3}$$

2) D(y,t) represents hyperbolic discounting if:

$$\boldsymbol{D(y,t) = \frac{1}{1+rt},\;\; r > 0} \tag{6-4}$$

The two models tend to be highly correlated; however, research has demonstrated that a hyperbolic model improves model fit to the data (Hardisty et al., 2013; Myerson & Green, 1995, Zhang & Rashad, 2008). Especially in terms of health, where individuals value imminent gratification, a hyperbolic discounting rate may be more appropriate.

6.2 Discounting and obesity

When individuals aim to maximise their utility, they make decisions about diet and physical activity which directly impact their weight. They are inherently trading off the disutility that arises from excess weight and its future health consequences for the pleasure (utility) they derive from eating at will and not engaging in physical exercise (Courtemanche et al., 2015b). Time preference is the amount of future utility that is equal to current utility. In terms of time preferences, people are choosing high-calorie, inexpensive and unhealthy food in lieu of delayed access to home-cooked healthier meals (Rasmussen et al., 2010). It has been theorised that obese individuals may react with more impulsivity.

Although the rise in obesity may also be a result of increases in the marginal rate of time preferences (Lakdawalla & Philipson, 2009), an opposing argument is that the mode of causation does run the other way; variations in health cause differences in the rate of time preferences (i.e., obesity influences time preferences) (Becker & Mulligan, 1997). This implies that healthy people expect to live longer and therefore have lower discount rates. It is theorised that the 'discount rate might be non-monotonically associated with body weight', as underweight individuals are also present- biased (Ikeda et al., 2010).

It has been hypothesised that individuals who have present-focused time preferences are more likely to be obese, because of the low value placed on future health outcomes. The negative health impacts (loss of health and longevity) occur in the future and the satisfaction of consuming unhealthy foods and using time for things other than exercise occurs in the present (Gray, 2011). Komlos et al. (2004, p.209) suggest that researchers 'explore the possible link between obesity and time preference, as important insights are likely to result'. Overall, the literature suggest that individual discount rates may impact obesity through behavioural pathways. Three behavioural aspects of time discounting are suggested as important.

- **Impatience:** overweight people are more focused on the present and therefore impatient, leading to higher discount rates.
- **Hyperbolic discounting:** overweight people discount the immediate future more than the distant future and this can be described by a hyperbolic function versus an exponential function.
- **Sign effect:** individuals discount future negative losses at a rate lower than positive gains in the future, meaning they require a lower rate when borrowing compared to saving money.

In normal weight individuals, the sign effect causes individuals to employ self-control around what foods to consume and to seek to prevent the future negative consequences of weight gain. Ikeada et al. (2010) demonstrated that body mass status was positively associated with impatience and hyperbolic discounting but negatively associated with the sign effect, and that those with higher body mass had higher discount rates.

6.3 Review of the literature

The two approaches to evaluating time preferences in the literature are (1) using proxies to represent time preferences, such as consumer savings/debt data or measurement of scales of time orientation, such as the Zimbardo Time Perspective Inventory (ZTPI)/Considerations of Future Consequences Scale (CFSC), and (2) survey data which asks respondents to make trade-offs based on hypothetical scenarios. The research using delay discounting (DD) techniques to compare obese and non-obese individuals has produced mixed results (Bickel et al., 2014). The studies using proxy measures indicate a relationship between consumer debt/savings and obesity, but there are other simultaneous factors that prove difficult to disentangle. The search strategy can be found in Appendix 21.

6.3.1 Proxies for time preferences

Komlos et al. (2004), using the National Health and Nutrition Examination Study (NHANES) undertaken between 1970 and 2000, found that the (lagged) savings rate fell and consumer debt increased alongside an increase in the prevalence of obesity (Komlos et al., 2004). Smith et al. (2005), using the same data, found a small effect of dissaving and obesity. This finding was also significant for particular ethnic and gender subgroups (black and Hispanic men and black women). A further study using savings rates with a large sample (N=15,591) from a UK survey found a negative relationship between being a saver and three measures of body fat (BMI, body fat percentage and waist circumference), with a larger effect in woman (Brown & Biosca, 2016).

Borghans and Golsteyn (2006), using a household survey in the Netherlands, found that the association between time preferences and BMI was stronger in men than women, applying the CFCS to represent time preferences. Other studies that similarly used the CFCS to represent time perspective found the CFCS to have only a small effect on BMI (Adams & Nettle, 2009; Adams & White, 2009) and a small effect of time preferences on the risk of becoming obese (Gray, 2011).

Those studies that used the ZTPI to represent time-orientation found that greater present-fatalistic scores (hopeless attitude toward life) were associated with greater BMI, while those respondents more present-focused on enjoyment and pleasure had lower BMI (Griva et al., 2015). In a similar study, only 18–24 year old respondents had more present-seeking scores associated with obesity (Guthrie et al., 2014). Conversely, Adams and White (2009) did not find any associations between BMI and the scores from the ZTPI.

One of the more comprehensive studies, that of Ikeda et al. (2010), used a Japanese Household Survey on Consumer Preferences and Satisfaction (2005) to demonstrate that an increase in impatience was associated with an increase in BMI. Similarly, Zhang and Rashad (2008) used a measure of willpower as a marker for time preferences, with results showing a weak association between time preferences focused on the present and higher BMI (Zhang & Rashad, 2008).

6.3.2 Delay discounting measures

A study using computerised elicitation methods to observe delay discounting in the USA, found that obese women discounted more than normal weight women (Weller et al., 2008). A similar result was found in a study of 'ready-to-eat and away-from-home foods'; overweight and obese women who had higher discount rates ordered more energy-dense food (Appelhans et al., 2012). Likewise, a study using hypothetical food and monetary delays observed that higher body fat percentage was associated with greater discounting for food rewards, but not monetary rewards (Rasmussen et al., 2010).

Chabris et al. (2008), using a delay discounting task, found a weak correlation between discount rate and BMI. Conversely, studies by Borghans and Galsteyn (2008), Adams and White (2008) and van der Pol (2010) did not find any correlation between delay discounting and BMI. A large study using a crowdsourcing service to recruit over 1,000 participants used both delay discounting and probability discounting questions, suggesting larger samples may detect differences in time preferences between obese and normal weight individuals (Bickel et al., 2014).

Table 6.1 outlines published studies assessing the relationship between time preferences and weight. It appears that those studies that use proxies for the discount rate, such as savings behaviour, debt-to-income ratios, self-reported willpower etc., demonstrate a relationship between obesity and discount rates (Komlos et al., 2004; Zhang & Rashad, 2008; Smith et al., 2005). One drawback of using proxies is that the savings rate may not fully capture individuals' time preferences. Some studies that used time preference questions to elicit discount rates also suggest a relationship between the time preferences and BMI (Chabris et al., 2008; Weller et al., 2008; Bickel et al., 2014), while other studies did not find any association between discounting and BMI (Borghans & Golsteyn, 2006; Adams & Nettle, 2009; van der Pol, 2010).

Table 6.1 Time preference studies of BMI or Obesity

Study	Sample	Data	Time preference measure	Dependent variable	Result
Adams and Nettle (2009)	N=804 UK	Postal questionnaire	CFCS	BMI_c	CFCS score associated with BMI (Lower BMI consider future more)
Adams and White (2009)	N=423 USA	Web based questionnaire	CFCS ZTPI TP hyperbolic	BMI_{log}	Only CFCS score was associated with BMI
Appelhans et al. (2012)	N=78 USA	Medical centre survey	DD	BMI	DD did not predict energy intake
Bickel et al. (2014)	N=1163 USA	Crowdsourcing survey	DD PD	BMI<25 25≤BMI<30 BMI≥30	Temporal discounting associated with obese (small)
Borghans & Galsteyn (2006)	N=2052 Netherlands	DNB Household survey	TP rate, CFCS	BMI_c	Discount rate variables not found to be significant with BMI.
Brown & Biosca (2016)	N=15,591	Understanding Society survey	Savings rate	BMI WC BF%	All measures negatively associated with saver (larger for women)
Chabris et al. (2008)	N=555 USA	Laboratory task	Delay discounting	BMI	Relationship between DR and BMI weak
Gray (2011)	N=5217 Netherlands	DNB Household survey	CFCS	BMI Obese	More present oriented preferences associated with greater BMI.
Griva et al. (2015)	N=413 Greece	Web Survey	ZTPI	BMI_c	Greater present focused scores were associated with greater BMI
Guthrie et al. (2014)	N=790 US	Community based survey	ZTPI	Obese	Present focused scores in obesity in 18-24 year olds
Hendrickson & Rasmussen (2013)	N=1,304 US	Computer survey	ZTPI	BF%	High BF% predicted for impulsive choice for food
Ikeda et al. (2010)	N=2,870 Japan	JHS 2005	DR or proxy of debt	BMI_c BMI > 25, BMI > 30	Connection between time preferences and BMI
Komlos et al. (2004)	N=N/R US	(NHANES)	Savings rate	Obesity	Negative association between obesity and savings rate
Rasmussen et al. (2010)	N=60	Computer discounting tasks	TP questions and food delay questions	BF%	BF% predicted discounting for food but not money
Smith et al. (2005)	N=~30 M USA	NLSY (1979)	Savings variable	BMI_c BMI>30	Positive association between discounting and weight for black men/women and Hispanic men
Weller et al. (2008)	N=112 USA	Delay discounting computer tasks	TP questions – money task	Obese	Obese women have greater delay discounting
van der Pol (2010)	N=1849 Netherlands	DNB household survey	TP questions Risk attitude	BMIc	Controlling for TP attenuates relationship between education and BMI – no direct effect
Zhang & Rashad (2008)	N=1202 US	2004 Roper Center Obesity survey data	Measure of willpower	BMIc Obese	Association between lack of willpower and BMI/probability of obesity

ZTPI: Zimbardo Time Perspective Inventory, CFCS: Consideration of Future Consequences Scale, BF%: Body fat percentage, DD: delay discounting, PD: probability discounting, NLSY: National Longitudinal Survey of Youth, NHANES: National Health and Nutrition Examination Study, JHS: Japan Household Survey on Consumer Preferences and Satisfaction.

There does appear to be a gender difference with regards to time preferences. Weller et al. (2008) observed that obese women had higher discount rates than normal weight women, but no difference was found between obese and normal weight men. Similarly, Appelhans et al. (2012) found that obese and overweight women with higher discount rates have higher caloric intake than obese and overweight women with lower discount rates.

Interestingly, there is no evidence that discount rates have been increasing over time along with obesity rates. A meta-analysis of time preferences from 1978–2002 found that time preferences have not changed over time (Percoco & Nijkamp, 2009). A similar finding using proxy variables (CFCS) from Borghans and Golsteyn (2006) found no evidence of changes in time preferences and the authors suggest that the upward trend in BMI is explained by high discounters gaining more weight. Overall, the current evidence shows a weak relationship between more present-focused preferences and increased BMI.

6.4 Research questions

This chapter examines whether there is an association between differences in the rate of time preference and a person's weight. The research will focus on the following questions:

Do overweight and obese individuals discount time differently from normal weight individuals, such that:

1. higher time preferences are associated with higher body mass?
2. overweight or obese individuals discount health differently to money?
3. overweight/obese individuals have different opinions on public policy directed towards reducing obesity?

6.5 Methods

Temporal discounting rates were estimated using hypothetical choice tasks between an immediate reward and a distant reward. Previous studies have employed two general approaches to estimate the rate of time preferences: (1) the matching method, where respondents are asked to provide the exact future amount they would require to be indifferent to the amount now, and (2) the multiple-staircase elicitation method, which forces respondents to make a number of binary choices between a reward now and a reward in the future, with an increase in the future reward after each choice.(Hardisty et al., 2013).

Studies have found that the matching elicitation method tends to result in lower discount rates (Hardisty et al., 2013). Furthermore, the matching method may cause inflated mean discount rates if respondents report implausible values. Nevertheless, the current research does not indicate which method should be employed, as all methods do express respondents' preferences. Both elicitation methods were explored during the focus group session and it was decided to use the multiple staircase elicitation method, as respondents found the task easier to comprehend (since they only had to compare two known values) and it is relatively simple to program these types of questions into the Survey Engine software.

6.5.1 Time preference survey questions

As part of the survey conducted in Chapter 5, four scenarios were included to evaluate the time preferences of respondents. See sections 5.9 and 5.10 for details about the survey collection and online panel. The presentation of the questions to respondents in Survey Engine can be found in Appendix 22.

Four hypothetical choice tasks were developed based on the multiple staircase methods, adapted from Rachlin et al. (1991). This method elicits individual's indifference points between a reward now (of value x) versus a reward (of value $> x$) in the future. By controlling the dollar amounts displayed to respondents, the discount rates can be selected during the survey design. The four questions assessed a monetary benefit, a monetary penalty, a health benefit and a weight-loss program with a monetary reward.

Scenario 1: Discount rate

The first scenario asked respondents to imagine that they could choose between receiving $500 now or another amount ($500 + x) one year from now. In the first example, respondents were asked to choose between $500 now and $510 one year from now. If the respondent chose $510 (which indicates their point of indifference is between $500 and $510 in one year) the question was considered complete and they were told Question 1 was over and shown Question 2. Those respondents who chose $500 were then presented with the choice between $500 now and $525 in one year. If respondent continued to choose $500 now, the yearly amounts increased to $550, $600, $800 $1,000 and finally $5,000. Once respondents chose the higher amount, they were told the question was over and continued to the next question. The question ended at $5,000 even if the respondent never chose the higher amount (i.e., they always chose $500 now, rather than $5,000 in 1 year).

Box 6.1 Scenario 1: Monetary reward

Imagine you could choose between receiving <u>$500 now</u>, or <u>another amount 1 year</u> from now.

A) Please indicate which option you would choose:

- ○ **Receive $500 now**
- ○ **Receive $510 in one year from now**

Scenario 2: Process disutility

The second scenario asked respondents to imagine that they have been caught speeding by the police and they can either pay the $200 speeding fine immediately or pay a different amount in six months from now. The first scenario asked respondents to choose between paying the $200 fine now or paying $400 in six months. Those who chose to pay $400 in six months time were told Question 2 was over and shown Question 3. Those who chose $200 now were shown the second scenario of paying $200 now or $300 in six months. The scenarios continued with decreasing amounts of $275, $250, $225, $220, $210, $200 and $150. It was hypothesised that there would be a proportion of respondents who would prefer to pay the $200 fine immediately, rather than wait six months to pay a reduced fine of $150, to negate the administrative burden of waiting to pay the fine. There is evidence that negative events are discounted differently as waiting for a negative event to occur causes discomfort, which individuals wish to avoid (Molouki et al. n.d.).

Box 6.2 Scenario 2: Monetary penalty

Imagine that you have been caught speeding by the police. You can either pay the $200 speeding fine immediately, or pay a different amount in 6 months from now.

A) Please indicate which option you would choose:

- ○ **Pay the $200 fine now**
- ○ **Pay $400, 6 months from now**

Scenario 3: Health-related benefit

The third scenario asked respondents to imagine they have pain and discomfort in their knee that limits their walking and their doctor recommends an operation on their knee to reduce the pain and help with their mobility. Respondents were then told that the operation was not urgent, and they have two options in terms of cost and waiting times: (1) the operation will cost $500, but they will need to wait 12 months for treatment, or (2) the operation will cost $2,000, but the waiting time is shorter. The first scenario asked the respondents to choose between waiting 12 months for the operation and paying $500 or waiting 10 months for the operation and paying $2,000. Those who chose the second option were told the question was over and presented with the fourth time preference question. Those who chose to wait 12 months were then presented with decreasing waiting time periods of eight, six, four, two and one month/s, with a final option of paying $2,000 for the operation immediately. As soon as the respondents chose a shorter waiting period, the question ended, and they were presented with the fourth and final time preferences question.

Box 6.3 Scenario 3: Health-related

Imagine you have pain and discomfort in your knee that limits your walking. Your doctor thinks that you need an operation on your knee to reduce the pain and help with your mobility.

The operation is not urgent and you have two options in terms of cost and waiting times:

- **Option 1: the operation will cost $500, but you will need to wait 12 months for treatment.**
- **Option 2: the operation will cost $2000, but the waiting time is shorter.**

A) Please indicate which option you would choose:

- ○ **Wait 12 months for the operation and pay $500**
- ○ **Wait 10 months for the operation and pay $2000**

Scenario 4: Exercise disutility

The final time preferences scenario asked respondents to imagine that they were overweight and that, to help them lose weight, the government is willing to provide a $300 incentive to enrol in a free weight-loss program. They are then told that the incentive will be paid once they enrol in the program and is not conditional on them losing weight. Alternatively, the government is offering another scheme that pays a higher cash incentive, but the payment is only available if they lose an agreed amount of weight. The first scenario was (1) a guaranteed $300 cash incentive now, or (2) $300 in six months from now, conditional on losing five kilograms. The respondents were then presented with increasing amounts of $310, $350, $400,

$500, $600, $800 and $1,000, conditional on losing five kilograms in six months. If they chose the higher amount they were then told that was the end of the question and presented with the feedback section of the survey. The question ended at $1,000 irrespective of whether the respondent chose $300 now or $1,000 in six months.

Box 6.4 Scenario 4: weight-loss program

Imagine that you are overweight. To help you lose weight, the Government is willing to provide a $300 incentive to encourage you to enroll in a free weight loss program. This incentive is paid to you once you enroll in the program, and is not conditional on you losing weight.

Alternatively, the Government is offering another scheme that pays a higher cash incentive, but the payment is only available if you lose an agreed amount of weight (e.g. 5 kilograms).

Which option would you choose?

- **Option 1: the guaranteed $300 cash incentive now, or**
- **Option 2: the higher amount 6 months from now, which is conditional on you losing weight?**

A) Please indicate which incentive you would choose:

- ○ **Receive $300 now**
- ○ **Receive $300 6 months from now, if you lose 5 kgs**

A range of values were used in each time preferences question to elicit discount rates across respondents. Table 6.2 summarises the values that were included in the four time-preference questions. The respondent would see an additional option until the point at which they were indifferent, at which time they moved forward to the next time preference question.

Table 6.2 Values presented in time preference questions

Question 1	Question 2	Question 3	Question 4
Receive $500 now or $x in one year:	**Pay $200 fine now or $x in 6 months:**	**Pay $500 in 12 months or $2,000 for operation in:**	**Receive $300 now or $x in 6 months if 5kg lost:**
$510	$400	10 months	$300
$525	$300	8 months	$310
$550	$275	6 months	$325
$600	$250	4 months	$350
$800	$225	2 months	$400
$1,000	$220	1 month	$500
$5,000	$210	Now	$600
	$200		$800
	$150		$1,000

Pilot data

Before the final survey went to field, a focus group session and multiple pilots were conducted to ensure that respondents could comprehend the choice tasks and to determine that the appropriate range of values were available to ensure balance across the trade-off options (i.e., that there was balance between the number of respondents that chose the first option and the number that choose the last option). Details of the pilots can be found in Appendix 13.

6.5.2 Econometric Analysis

An econometric analysis was conducted to determine whether respondents' rate of time preference could explain differences in weight. Specifying BMI as a continuous variable, the following model was estimated:

$$\boldsymbol{BMI_c = \beta_0 + \beta_1 DR + \beta_2 C + \varepsilon} \tag{6-5}$$

In equation (6-6), *DR* represents the discount rate used (for each of the four questions) and *C* is a vector of control variables. Another way of analysing the data is logit models, in which the focus is on whether respondents are obese or not. In this case, the dependent variable is binary and coded as a 0 or 1 and the following model estimated:

$$\boldsymbol{Pr(Obese = 1 \mid) = \left[1 + e^{-(\beta_0 + \beta_1 DR + \beta_2 C)}\right]^{-1}} \tag{6-6}$$

In equation (6-7), the probability of being obese is a function of the respondents' discount rate (*DR*) and other sociodemographic variables (*C*). Table 6.3 summarises the models that were conducted to test the association between respondents' discount rates and BMI or the probability of being obese. The initial analyses estimated models without any control variables. Full models controlling for covariates were also estimated.

Table 6.3 Econometric models estimated

	Dependent variable	Discount Rate	Control variables	Analysis
Model 1	BMI (continuous)	Continuous (DR1/2/3/4)	None	OLS
Model 2	Obese (probability)	Continuous (DR1/2/3/4)	None	logit
Model 3	BMI (continuous)	DR 1/2/3/4 groups	None	OLS
Model 4	Obese (probability)	DR 1/2/3/4 groups	None	logit
Model 5	BMI (continuous)	Continuous (DR1/2/3/4)	Yes	OLS
Model 6	Obese (probability)	Continuous (DR1/2/3/4)	Yes	logit
Model 7	BMI (continuous)	DR 1/2/3/4 groups	Yes	OLS
Model 8	Obese (probability)	DR 1/2/3/4 groups	Yes	logit

6.5.3 Dependent variables

The dependent variables used in the analyses were based on weight or obesity. In some models, BMI was estimated (as described in Chapter 5) and used as a continuous variable. In other models, a dummy variable was created indicating 1 if the respondent was considered obese/severely obese and 0 if the respondent was underweight/normal weight/overweight. Preliminary analysis comparing the five weight categories demonstrated that these were the most appropriate combinations.

6.5.4 Discount rate calculations

For each of the scenarios, the estimated discount rates were calculated by estimating the indifference point between the two scenario options presented to respondents. The nature of the questions, with forced-choice options where individuals eventually switch to choose the larger amount, results in an 'indifference point' between the two values. For example, in the first scenario, if respondents switched on the third option ($500 now vs $550 in one year), their indifference point lies somewhere between the second option ($525 in one year) and the third option ($550 in one year). Therefore, for each discount rate calculated, the indifference points were calculated as the average of the upper and lower bound (the mid-point between each scenario). To evaluate the association between BMI (and obesity status), the following model was used:

$$\boldsymbol{V_p = V_f + (1 + \delta)^{t-1}} \tag{6-7}$$

where V_p is the present value, V_f is the future value and δ is the discount rate (Hardisty et al., 2013). The greater the discount rate, the more present-oriented an individual's preferences. For each option in each scenario, the indifference points were converted into discount rates, using an exponential model and a hyperbolic model. Both models were estimated, as it is not conclusive in the literature which distribution better represents people's preferences. The discount rates were calculated using the following formulas, where V_p is the present value, V_f is the future value and *t* is the delay (in years).

Exponential model:

1) $$\boldsymbol{DR_{exp} = \left(-\frac{1}{t}\right) ln\left(\frac{V_p}{V_f}\right)} \tag{6-8}$$

Hyperbolic model:

2) $$\boldsymbol{DR_{hyp} = \left(\frac{V_f}{V_p}\right)^{\frac{1}{t}} - 1} \tag{6-9}$$

Table 6.4 summarises the discount rates calculated for each of the scenarios in each of the time preference questions.

Table 6.4 Discount rates from time preferences survey

Question 1			
Receive $500 now or:			
Reward in 1 year	**Hyperbolic DR**	**Exponential DR**	**Number of respondents**
$510	1.0%	1.0%	13.6%
$525	2.5%	2.5%	8.4%
$550	5.0%	4.9%	12.5%
$600	10.0%	9.5%	18.9%
$800	30.0%	26.2%	21.8%
$1,000	50.0%	40.5%	13.0%
$5,000	450.0%	170.5%	7.1%
$500 now always	n.e	n.e	4.7%
Question 2			
Pay $200 fine now or:			
Payment in 6 months	**Hyperbolic DR**	**Exponential DR**	**Number of respondents**
$400	300.0%	81.1%	7.8%
$300	125.0%	44.6%	3.5%
$275	89.1%	34.4%	3.7%
$250	56.3%	23.6%	3.9%
$225	26.6%	12.1%	7.3%
$220	21.0%	9.8%	3.9%
$210	10.3%	4.9%	8.1%
$200	0.0%	0.0%	25.8%
$150	–43.8%	–26.7%	26.0%
Pay $200 fine now	n.e	n.e	10.1%
Question 3			
Pay $500 to have knee operation in 12 months or:			
Pay $2000 to have operation sooner	**Hyperbolic DR**	**Exponential DR**	**Number of respondents**
10 months	409500.0%	831.8%	10.1%
8 months	6300.0%	415.9%	5.3%
6 months	1500.0%	277.3%	9.3%
4 months	700.0%	207.9%	6.3%
2 months	427.8%	166.4%	6.8%
1 month	353.7%	151.2%	6.1%
Now	300.0%	138.6%	6.1%
Pay $500	n.e.	n.e.	49.9%
Question 4			
Receive $300 now when enrolling in the weight-loss program or:			
Receive reward in 6 months if lose 5 kgs	**Hyperbolic DR**	**Exponential DR**	**Number of respondents**
$300	0.0%	0.0%	28.9%
$310	6.8%	6.6%	4.9%
$325	17.4%	16.0%	3.4%
$350	36.1%	30.8%	8.3%
$400	77.8%	57.5%	11.1%
$500	177.8%	102.2%	13.0%
$600	300.0%	138.6%	9.2%
$800	611.1%	196.2%	5.3%
$1,000	1011.1%	240.8%	7.0%
$300 now	n.e.	n.e.	8.7%

Note: n.e. refers to discount rates that were not estimable as the discount rate can reach infinity

6.5.5 Control variables

All the models were controlled for sociodemographic and economic variables that could also impact on BMI or discount rates. Age, gender, education, marital status, work status, health status, medical condition, activity levels, smoking status, drinking status were all included in the model. Further specifications of the variables are described below.

Age groups

The age groups used in the models were taken from the survey. The following categories were created: (1) 15–24 years, (2) 25–34 years, (3) 35–44 years, (4) 45–54 years, (5) 55–64 years, (6) 65–74 years, (7) 75+ years.

Gender

Five respondents reported their gender as ‘other’; the gender variable was modified to male/female by combining those who reported ‘other’ with ‘male’. Testing demonstrated that there were no statistically significant differences between the genders in terms of BMI.

Income variable

The income variable was modified into five different groups representing low, low-mid, mid-high, high, unknown: (1) negative or zero–$19,999 a year, (2) $20,000–$79,999 a year, (3) $80,000–$149,000 a year, (4) over $500,000 a year and (5) respondents who said, ‘don’t know’ or ‘prefer not to say’.

Education

The education variable was modified into three groups representing: (1) Year 12 or below, (2) certificate (any level including trade certificate), diploma or advanced diploma, and (3) bachelor’s degree, honours degree, graduate diploma, graduate certificate, postgraduate degree (masters or doctorate).

Work status

A second work status variable was constructed into six groups to represent (1) full time/part time paid work or self-employed, (2) retired, (3) disabled/sick or unpaid work, (4) studying, (5) unpaid housework or unemployed, and (6) other. These groups were combined based on analysis that determined which groups were not statistically different to each other in terms of their effect on BMI.

Marital Status

The question asking respondents about their current living situation was grouped to represent (1) Single, never married, (2) Married or living with a partner, (3) Divorced, separated, widowed or those who preferred not to say.

Health status

The health status question included in the survey asked respondents to report on their general health. The five levels (from 1 to 5) were excellent, very good, good, fair or poor health.

No Medical condition

A dummy variable was included in the model to represent respondents who did not report having a medical condition.

Smoking status

A dummy variable to represent respondents' smoking status was included in the model. Respondents who stated, 'I have never smoked' or 'I used to smoke but no longer smoke' were coded as 0. Respondents who stated, 'I smoke everyday', 'I smoke at least weekly (but not daily)' or 'I smoke more or less often than weekly' were coded as 1. It is important to include smoking status in the analysis for two reasons: (1) smoking supresses the appetite, which may impact BMI, and (2) people who smoke may discount time differently (Bickel et al., 1999). A positive relationship between BMI and discount rates may be underestimated if the negative correlation with smoking is not accounted for.

Drinking status

A dummy variable to represent respondent's alcohol consumption was included in the model. A current drinker (recorded as 1) was represented by those who stated in the survey 'I drink alcohol everyday', 'I drink at least weekly (but not daily)', 'Yes, but only rarely'. Respondents who stated, 'I never drink alcohol' or 'I used to drink but no longer drink' were coded as 0. It was important to control for drinking status, as research demonstrates that heavy drinking is associated with higher discounting compared to comparison groups (Vuchinich & Simpson, 1998).

Physical activity

The question in the survey asking respondents about their participation in moderate activities was included in the model to control for the impact of exercise (or inactivity) on weight. The levels represented how often they participated in moderate activities or exercise (such as walking, bowling or playing golf) with levels being (1) not at all, (2) less than once a week, (3) 1–2 times a week, (4) 3–6 times a week, or (5) every day.

6.5.6 Regression diagnostics

Multiple diagnostic tests were conducted to ensure the models estimated met the assumptions of the estimated models.[57]

Heteroskedasticity

The assumption underpinning the econometric analyses was that the variance of the error term was constant (homoskedastic). If this assumption is violated, and there is the presence of heteroskedasticity, the estimated standard errors will be biased. One method to detect heteroskedasticity is visual inspection of the residuals compared to the fitted values. Figure 6.1 displays the results of a residual-versus-fitted (rvf) plot in Stata.

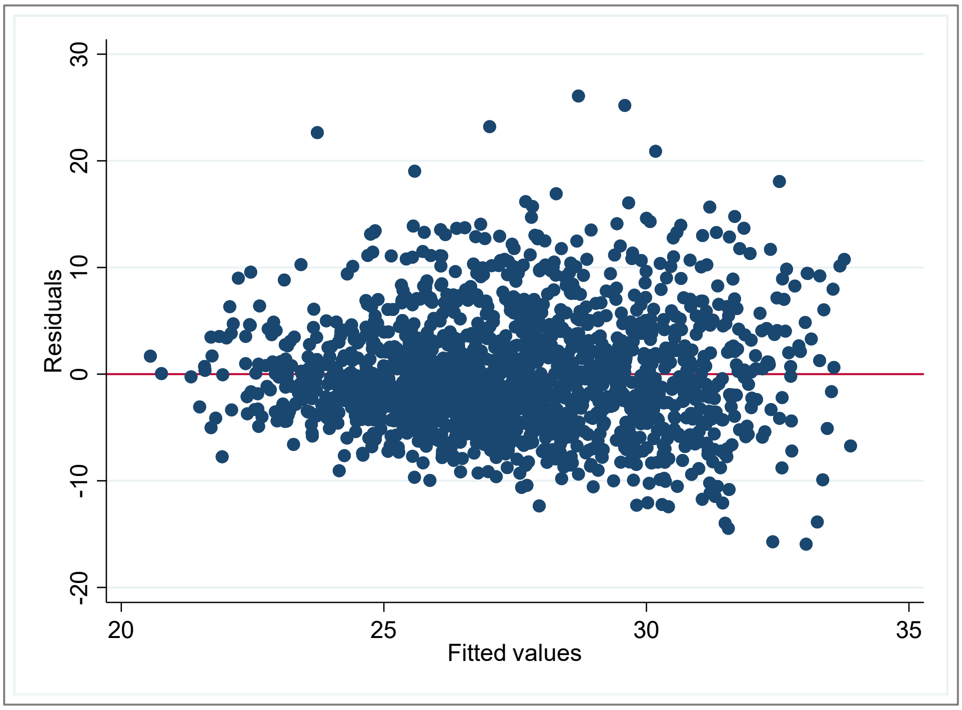

Figure 6.1 Residuals versus fitted values

Based on the rvf plot, there appears to be some heteroskedasticity, as the distribution of residuals widens for larger fitted values. Tests in Stata were run to test for heteroskedasticity after model specification. The residuals of the model were not distributed normally; therefore,

[57] UCLA Institute for digital research and education: Regression diagnostics- https://stats.idre.ucla.edu/stata/webbooks/reg/chapter2/stata-webbooksregressionwith-statachapter-2-regression-diagnostics/

the default Breusch-Pagan test in Stata to test for linear forms of heteroskedasticity is not appropriate. White's general test for heteroskedasticity was used instead, with the 'estat imtest, white' command in Stata. The result was a rejection of the null hypothesis of homoskedasticity, and therefore robust standard errors were specified in the models. Specifying robust standard errors relaxes the assumption that the errors are iid.

There is no test for heteroskedasticity for binary choice models in Stata (such as logit and probit models). The estimators in a non-linear model are estimated by a maximum likelihood estimator, which makes the detection of heteroskedasticity difficult. Given that there is no current test for the logit models in Stata, the logit models were estimated without additional specification.

Observations with high influence

The leverage of the model was assessed to identify observations that have a greater impact on the coefficient estimates. Those respondents with a leverage greater than (2k + 2)/n (k is the number of predictors and n is the number of observations) were identified in the dataset as having a high leverage. Figure 6.2 displays those respondents with both large leverage and a large residual.

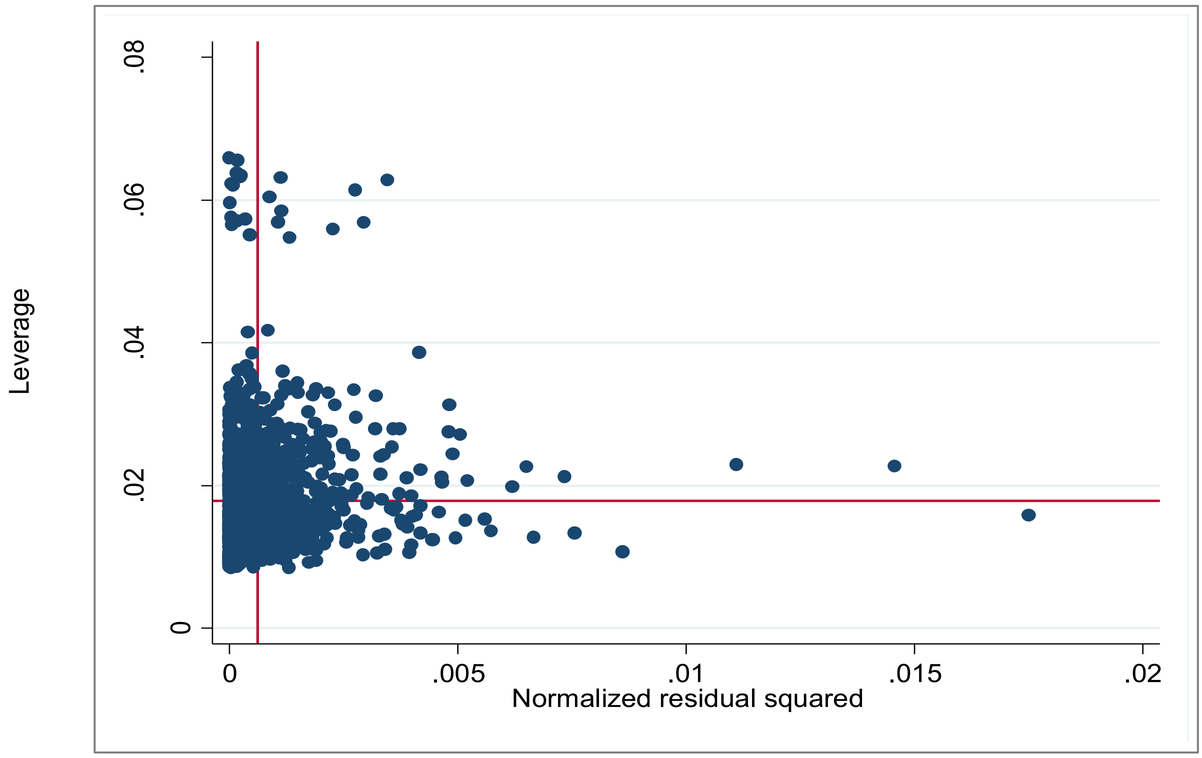

Figure 6.2 Respondents with high leverage and high influence

The reference axis lines indicate the mean leverage (horizontal) and the normalised residual squared (vertical). Using the ‘dfit’ command in Stata, those respondents with the most influence can be identified. Using a cut-off value of (2*sqrt(k/n)), those respondents with an influence greater than the cut-off were labelled in the dataset as a ‘bad-fit’ with a new generated dummy variable. In total, 98 respondents were considered to have the highest influence.

Omitted variable bias

Using the command ‘estat ovtest’ in Stata, the preliminary models in Stata were run to test if omitted variable bias was present. This test runs the ‘regression specification-error test’ to ensure the model has not been mis-specified. The null hypothesis of the test is that the model has no omitted variables. Through multiple iterations of specifying models with the data available in the survey, it was discovered that the presence of a medical condition was a significant variable impacting on BMI and the models performed better once this was controlled for.

Imperfect multicollinearity

Stata can test for multicollinearity within the model using the ‘estat vif’ command. After the regression, the variance inflation factor (vif) can be calculated and the rule of thumb is that a vif greater than 5 implies that imperfect multicollinearity is present in the model. Collinearity can also be explored using the correlation commands. In Stata, correlations greater than 0.8 is indicative of multicollinearity. In the survey data, there were no correlations great than 0.4, with the greatest correlation between age, health and no medical condition.

6.5.7 Sensitivity analyses

Sensitivity analyses were conducted. The first sensitivity analysis excluded the respondents who always chose the first option (e.g., $510 in one year rather than $500 now) for all four time- preferences scenarios. This was in case these respondents were not properly considering each question and clicking to the end of the survey. In the second sensitivity analysis, respondents who failed the DCE dominant question were removed. This scenario was deliberately included to test whether people were reading the questions or lacked understanding of the task (see Section 5.7.1 for a further description). In the third sensitivity analysis, those respondents who finished the entire survey in under three minutes and 45 seconds were removed (as discussed in section 5.11.4). In the final sensitivity analysis, respondents who had both high leverage and high influence were excluded from the analysis, as the diagnostic measures flagged these respondents as outliers who could potentially bias the model fit. Table 6.5 summarises the four sensitivity analyses conducted.

Table 6.5 Sensitivity analysis – time preferences

Model	Respondents removed	Description
SA 1	All '1' clicked	Respondents who chose 1 for all four time preferences questions and all scenarios within those questions.
SA 2	Failed DCE check	Respondents who failed the dominant DCE choice task
SA 3	Under 3 min, 45 sec	Respondents who finished the entire survey in under 3 min 45 sec
SA 4	Bad fit respondents	Respondents who were highlighted as having high leverage/influence

6.5.8 Public policy and feedback questions

The aim of this section of the survey was to collect opinions and views surrounding public policies to reduce the level of obesity in society, especially regarding whether the views of obese individuals differ from normal weight individuals. The questions asked were as follows:

1. How much of a problem is obesity to society? (Extreme problem, severe problem, moderate problem, slight problem or not a problem)
2. How much of a role should the government play in reducing obesity? (No role, minor role or a major role)
3. Should the government pay individuals who are overweight/obese an incentive to lose weight? (Yes or No)
4. Should the government tax unhealthy food and drink (e.g., a sugar tax)? (Yes or No)

The number of respondents and the proportions were calculated for each of the four public policy questions and feedback questions. The proportions for each BMI weight group were also calculated for the public policy questions to compare opinions between normal weight, overweight and obese individuals. A χ^2 test was conducted to test the differences between each of the questions by weight category. Comments from respondents can be found in Appendix 23.

6.6 Results

6.6.1 Dataset

The time preferences dataset was constructed using the data from the respondents who completed Pilot 3 (after changes to the questions) and the full sample. An additional nine respondents were marked as non-completers (either by 'user-initiated timeout' or 'system-initiated timeout') after they had answered all time preference questions. The total number of respondents included in the time preferences analysis was 1,627 (Table 6.6).

Table 6.6 Total responders

	Completers	Non-completers Full time preferences set	Time preferences Dataset
Pilot CHERE*	10	–	
Pilot 1*	104	–	
Pilot 2*	101	–	
Pilot 3	121	0	121
Full Sample	1,497	9	1,506
Total respondents	**1,833**	**64**	**1,627**

**Modifications were made to the time preference questions*

6.6.2 Summary statistics

The total number of respondents included in the time preferences dataset was 1,627. The demographic characteristics of these respondents compared to the Australian population are presented in Table 6.7. The data for the Australian population were sourced from ABS statistics for adults 18 years and over.

Table 6.7 Time preferences survey respondent demographic characteristics

Characteristic	Number of respondents	Percentage	Australian Population^
Total respondents	**1,627**		
Gender			
Female	719	44.2%	50.4%
Male	903	55.5%	49.6%
Other	5	0.3%	NR
Age			
18-24	181	11.1%	12.3%
25-34	335	20.6%	19.3%
35-44	276	17.0%	17.2%
45-54	247	15.2%	16.8%
55-64	293	18.0%	14.8%
65-74	215	13.2%	11.1%
75+	80	4.9%	8.5%
Aboriginal or Torres Strait Islander origin			
Yes	67	4.1%	3.4%
No	1560	95.9%	96.6%
Birth country			
Australia	1229	75.5%	66.7%
New Zealand	34	2.1%	2.2%
China	10	0.6%	2.2%
UK	125	7.7%	4.4%
Germany	18	1.1%	0.4%
Greece	2	0.1%	0.4%
Italy	7	0.4%	0.7%
Lebanon	4	0.3%	0.3%
Netherlands	10	0.6%	0.3%
Vietnam	11	0.7%	0.9%
Other	177	10.9%	21.3%
Aboriginal or Torres Strait Islander origin			
Yes	66	4%	3.4%
No	1583	96%	96.6%

^ ABS Demographic statistics: (Australian Bureau of Statistics, 2017a)

The socioeconomic characteristics of these respondents compared to the Australian population are presented in Table 6.8. The Australian socioeconomic statistics were sourced from the Household Income and Wealth Survey (2015–16) (Australian Bureau of Statistics, 2017c), the 2016 Survey of Education and Work (Australian Bureau of Statistics, 2016)and the 2016 Census of Population and Housing(Australian Bureau of Statistics, 2017b).

Table 6.8 Time preference survey respondent socioeconomic characteristics

Characteristic	Number of respondents	Percentage	Australian Population
Respondents	**1,627**		
Education			
Year 11 and below	239	14.7	26.0
Year 12	266	16.4	18.7
Certificate (any level)	337	20.7	18.8
Diploma/advanced	239	14.7	10.1
Bachelors/honours	342	21.0	17.9
Grad diploma/certificate	69	4.2	2.9
Postgraduate degree	135	8.3	5.6
Living situation			
Single, never married	408	25.1	
Married	783	48.1	47.0
Living with a partner	226	13.9	9.7
Divorced	120	7.4	
Separated	46	2.8	
Widowed	32	2.0	
Prefer not to say	12	0.7	43.3
Income			
Negative or zero income	21	1.3	1.2
$1–$19,999	114	7.0	1.5
$20,000–$49,999	384	23.6	20.3
$50,000–$79,999	304	18.7	15.7
$80,000–$109,999	245	15.1	12.4
$110,000–$149,999	190	11.7	20.3
$150,000–$199,999	91	5.6	9.1
$200,000 +	61	3.8	8.5
Don’t know	48	3.0	9.5
Prefer not to say	169	10.4	1.5
Work status			
Full/part time work	776	47.7	47.8
Self-employed	127	7.8	12.5
Retired	317	19.5	
Disabled/sick	51	3.1	
Unpaid work	14	0.9	
Studying	92	5.7	
Unpaid housework	135	8.3	4.5
Unemployed	93	5.7	6.8
Other (please specify)	22	1.4	28.4

Overall, the characteristics of the time preference dataset were similar to the Australian population. The noticeable differences were that the dataset had a higher percentage of respondents who were male, born in Australia and had higher levels of education. A comparison of the health characteristics of the survey respondents and the Australian population is presented in Table 6.9. As with the demographic characteristics, the respondents were similar to the Australian population in terms of height, weight and BMI. Their smoking status also reflected the national trend; however, a comparison of alcohol consumption is difficult due to the nature of the survey question, which differed from the National Health Survey questions (Australian Bureau of Statistics, 2015).

Table 6.9 Survey respondent weight and health characteristics

Characteristic	Mean	Australian population
Respondents	**N = 1,627**	
Height (cm)	**170.9**	**169.0**
Females	164.3	162.2
Males	176.1	176.1
Weight (kg)	**80.5**	**78.8**
Females	74.0	71.4
Males	85.6	86.4
BMI	**27.5**	**27.5**
Females	27.4	27.2
Males	27.5	27.8
Weight groups – All^		
Underweight	2.6%	1.6%
Normal weight	36.4%	35.0%
Overweight	33.0%	35.5%
Obese	16.8%	18.3%
Severely obese	11.2%	9.5%
Weight groups – Females		
Underweight	4.5%	2.1%
Normal weight	41.6%	41.7%
Overweight	24.1%	28.8%
Obese	15.4%	16.6%
Severely obese	14.5%	10.8%
Weight groups – Males		
Underweight	1.2%	1.2%
Normal weight	32.2%	28.1%
Overweight	40.2%	42.4%
Obese	17.9%	20.1%
Severely obese	8.5%	8.2%
Smoking status		
Never smoked	51.9%	52.6%
Used to smoke	28.9%	31.4%
Smoke everyday	14.8%	14.5%
Smoke at least weekly	2.0%	1.5%
Smoke less than weekly	2.4%	
Alcohol consumption		
Never drunk alcohol	11.0%	10.7%
Used to drink	13.5%	
Drink alcohol everyday	9.2%	17.4%
Drink at lease weekly	31.0%	
Drink only rarely	35.3%	

^ - Includes 5 respondents with 'other' gender

6.6.3 Discount rate analyses

A variable for each group for each of the four scenarios was derived to represent when a respondent chose their indifference point. There were some concerns with the continuous measurement for respondents who had infinite discount rates (and no indifference point), which could skew the distribution of the variable. Using the percentage of respondents that answered each option within the scenario removed any concerns about the calculations for each time-period and provided a ranking of the answers signifying ascending discount rates.

The percentage of respondents who answered each option in the four time-preference scenarios was calculated for each of the BMI groups. The significance between the groups was tested for each of the questions using the discount rate as a continuous variable as well as an ordered categorial variable. The percentage of respondents at each indifference point are presented in Figures 6.3, 6.4, 6.5 and 6.6.

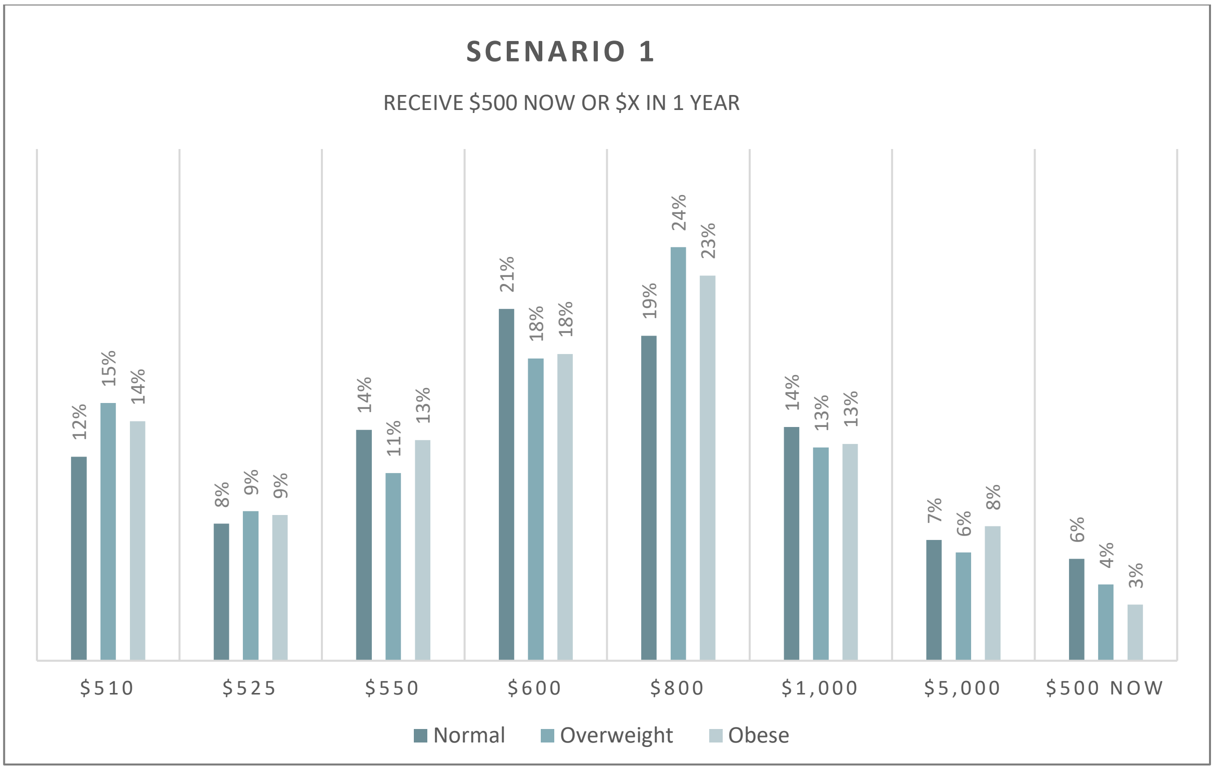

Figure 6.3 Monetary time preference scenario

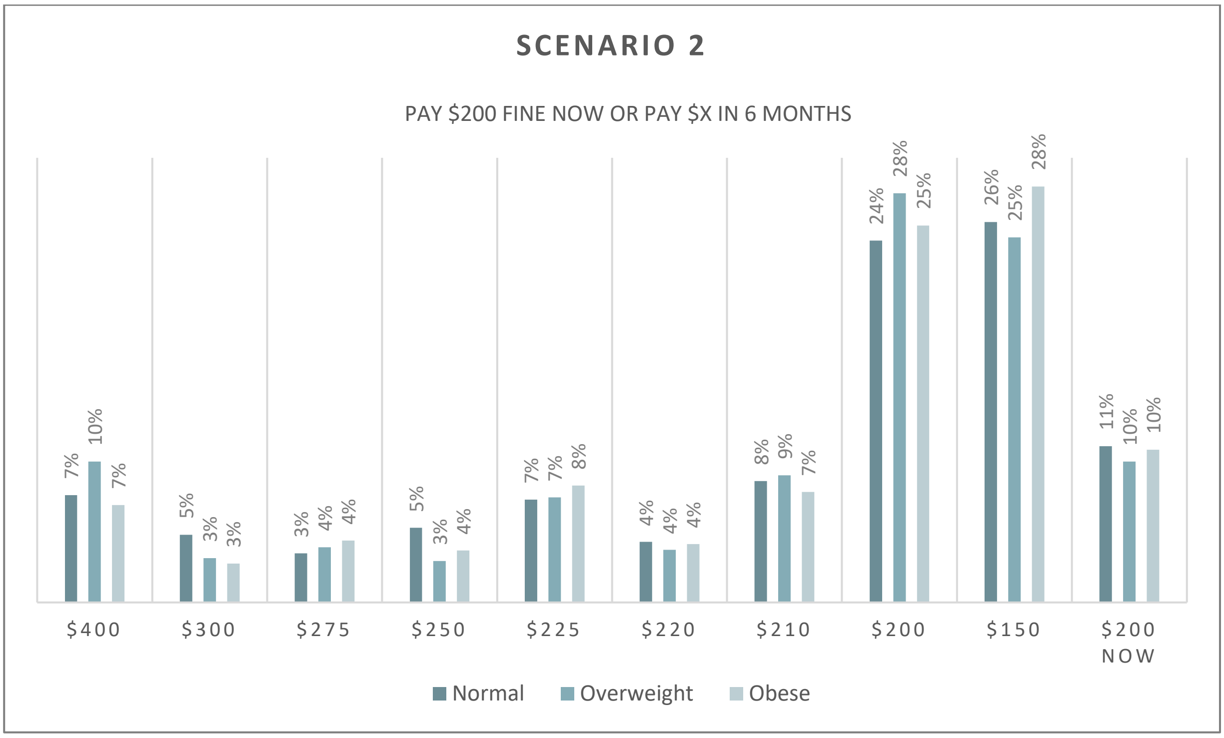

Figure 6.4 Monetary penalty time preference scenario

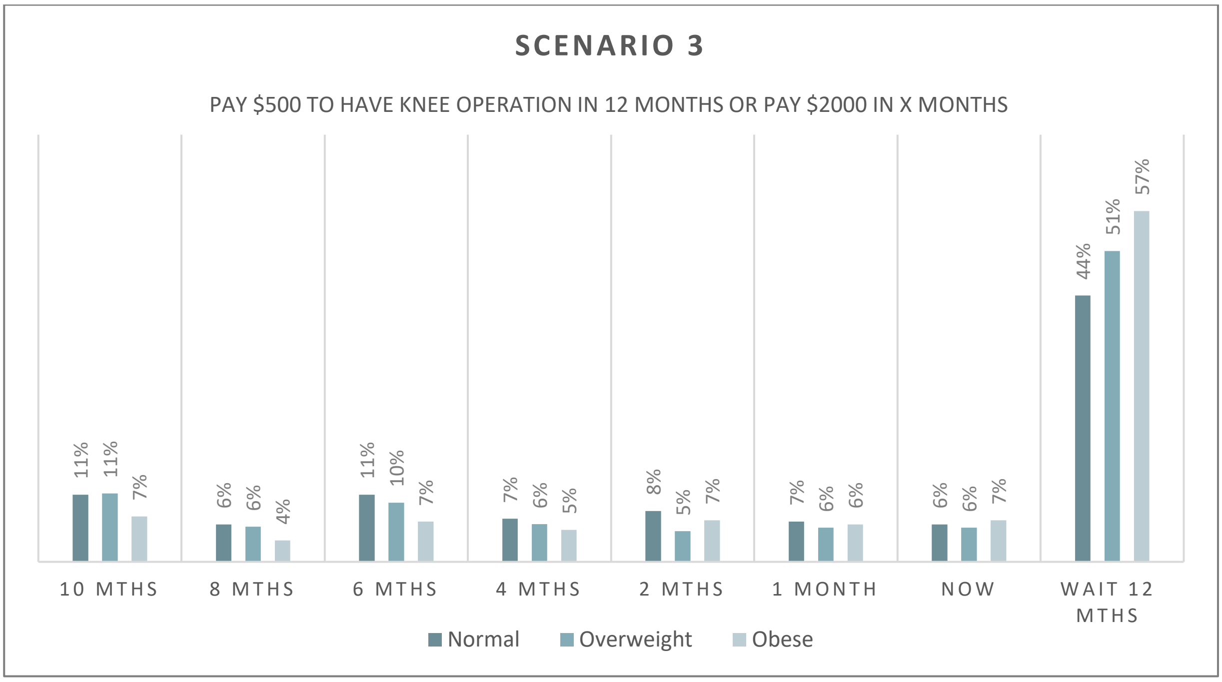

Figure 6.5 Health time preference scenario

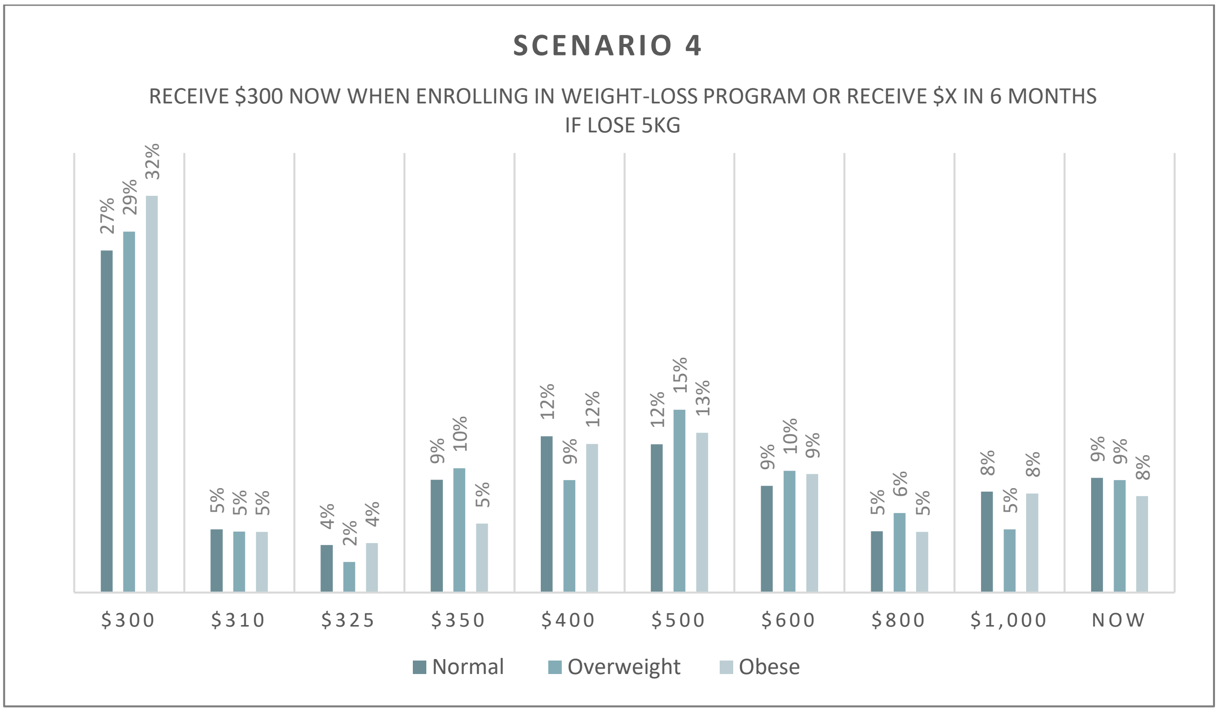

Figure 6.6 Weight loss time preference scenario

An analysis was conducted to compare the differences in the rate of time preference between the weight groups using a one-way analysis of variance test with a Bonferroni multiple comparison adjustment. The following were the only significant differences observed.

- Discount rate groups (multinomial): In scenario 3, obese respondents were significantly less likely to pay extra to reduce the waiting time for the operation compared to overweight and normal weight respondents.
- Discount rate (continuous): In scenario 3, the obese respondents' discount rates were significantly different (as above) from those of the overweight and normal weight respondents.

The only scenario that had significant differences between the weight groups was scenario 3. A further exploration using multinomial logit demonstrated that a significantly smaller proportion of obese individuals were willing to pay $2,000 to have the knee operation sooner compared to the normal or overweight individuals. Given that half of respondents in scenario 3 said they would wait 12 months for the operation and only pay $500, this choice task from scenario 3 was analysed separately. A significantly higher proportion of the obese respondents would choose to wait compared to normal or obese respondents. When using the Bonferroni adjustment, the obese and overweight respondents were significantly different to normal weight respondents, with more normal weight individuals willing to pay $2,000 for an earlier operation time. Looking at the inverse relationship, there was a significantly increased probability of being obese for those who chose to wait the full 12 months versus those who chose to pay for an earlier operation [0.322 vs 0.238 (p value < 0.000)]. Interestingly, this result is inconsistent with the literature reporting that obese individuals are more impatient. However, this could also be explained by income constraints for obese individuals, which this analysis did not control for, or simply that obese individuals value future health benefits differently. A further analysis was conducted comparing the answers for each of the time preference scenarios by gender. Females had higher discount rates for scenario 1 and lower discount rates for scenario 2, with similar discount rates for the health and weight loss discounting scenarios.

An interesting result was demonstrated in the weight loss time preference scenario. Almost a third of respondents (28.8%) chose the option of enrolling in a weight-loss program that paid a reward of $300 dollars in six months if they lost five kilograms, over the option of receiving $300 now to enrol in a weight-loss program. This indicates that respondents place a value on being held accountable (or being committed) to losing weight.

6.6.4 Mean discount rates

The mean and median discount rates for normal weight, overweight and obese respondents were derived from the estimated indifference points using both the exponential and hyperbolic discount rates that were calculated. Table 6.10 displays the discount rates for each weight category and the significance between groups.

Table 6.10 Mean discount rates by BMI category

	DR 1		DR 2		DR 3		DR 4	
	HYP	EXP	HYP	EXP	HYP	EXP	HYP	EXP
Mean								
Normal	0.59	0.31	0.39	0.19	458.21*	1.95***	1.31	0.54
Overweight	0.55	0.31	0.42	0.20	464.51*	1.81***	1.18	0.52
Obese	0.63	0.33	0.32	0.15	309.61*	1.36***	1.31	0.54
Non-obese	0.57	0.31	0.40	0.19	461.10*	1.89***	1.25	0.53
Obese	0.63	0.33	0.32	0.15	309.61*	1.36***	1.31	0.54
Median								
Normal	0.15	0.14	0.05	0.05	3.54***	1.51***	0.27	0.24
Overweight	0.15	0.14	0.05	0.05	0.00***	0.00***	0.27	0.24
Obese	0.15	0.14	0.05	0.05	0.00***	0.00***	0.27	0.24
Non-obese	0.15	0.14	0.05	0.05	3.00***	1.39***	0.27	0.24
Obese	0.15	0.14	0.05	0.05	0.00***	0.00***	0.27	0.24

**p<0.05, **p< 0.01, ***p<0.001*

It should be noted that the estimated mean discount rate for the third scenario is substantially greater than the other scenarios given the short time periods estimated and the constant difference between paying $2000 or waiting to pay $500. An analysis of variance using a Bonferroni command tested for differences between the different weight groups. In addition to the above analyses, a Wilcoxon rank-sum test was conducted to compare those who were obese to those who were not. A significant difference between obese and non-obese respondents was demonstrated, but only for the third time preference scenario. It appears that obese respondents had significantly reduced discount rates compared to normal weight respondents, with a larger proportion of obese than normal weight (57% vs 44%) choosing to not pay $2,000 to have the operation sooner.

6.6.5 Econometric results

An initial analysis was conducted to estimate the independent effect of discounting on BMI or the probability of being obese. Table 6.11 presents the results for Models 1 and 2 (using the continuous discount rates) and Models 3 and 4 (using discount rate groups) for time preference scenarios 1 and 2. All of the analyses presented use the indifference points calculated from the hyperbolic discount function, as the overall results did not change between the two discount functions.

Table 6.11 Regression results: Time preference scenarios 1 & 2 – Unadjusted

	DR1				DR2			
	BMI		Obese (OR)		BMI		Obese (OR)	
	β	SE	β	SE	β	SE	β	SE
Discount rate - continuous	***Model 1***		***Model 2***		***Model 1***		***Model 2***	
DR – log continuous	–0.054	(0.10)	0.981	(0.04)	-0.026	(0.16)	0.904	(0.06)
R2		*0.0002*		*0.0001*		*0.0000*		*0.0013*
LL		*–5195*		*–965*		*–5195*		*–964*
AIC		*10394*		*1934*		*10394*		*1932*
BIC		*10405*		*1945*		*10405*		*1943*
Discount rate - groups	***Model 3***		***Model 4***		***Model 3***		***Model 4***	
DR1 – $500 (base)	–		–					
DR1 – $525	–0.651	(0.63)	0.976	(0.23)				
DR1 – $550	–0.858	(0.56)	0.998	(0.21)				
DR1 – $600	–0.973	(0.54)	0.894	(0.18)				
DR1 – $800	–0.252	(0.51)	1.007	(0.19)				
DR1 – $1000	–0.328	(0.60)	0.924	(0.20)				
DR1 – $5000	–0.438	(0.76)	1.118	(0.28)				
DR1 – $500 now	–1.362	(0.80)	0.593	(0.19)				
DR2 – $400 (base)					-		-	
DR2 – $300					–1.806*	(0.91)	0.862	(0.33)
DR2 – $275					–0.159	(0.93)	1.500	(0.52)
DR2 – $250					–1.857*	(0.91)	1.101	(0.39)
DR2 – $225					0.037	(0.76)	1.420	(0.41)
DR2 – $220					–0.103	(0.98)	1.293	(0.45)
DR2 – $210					–0.737	(0.69)	1.122	(0.32)
DR2 – $200					–0.181	(0.59)	1.238	(0.29)
DR2 – $150					–0.415	(0.59)	1.403	(0.33)
DR2 – $200 now					–0.504	(0.73)	1.288	(0.35)
R^2/Pseudo R^2		*0.0042*		*0.0022*		*0.0059*		*0.0026*
LL		*–5192*		*–963*		*–5190*		*–963*
AIC		*10400*		*1942*		*10401*		*1945*
BIC		*10443*		*1985*		*10455*		*1999*

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Table 6.12 presents the results for Models 1 and 2 (using the continuous discount rates) and Models 3 and 4 (using discount rate groups) for time preference scenarios 3 and 4.

Table 6.12 Regression results: Time preference scenario 3 & 4 – Unadjusted

	DR3				DR4			
	BMI		Obese (OR)		BMI		Obese (OR)	
	β	SE	β	SE	B	SE	β	SE
Discount rate - continuous	***Model 1***		***Model 2***		***Model 1***		***Model 2***	
DR – log continuous	–0.0002*	(0.0001)	0.999*	(0.04)	-0.008	(0.07)	1.013	(0.03)
R2		*0.0025*		*0.0027*		*0.0000*		*0.0001*
LL		*–5193*		*–963*		*–5183*		*–964*
AIC		*10391*		*1929*		*10371*		*1931*
BIC		*10401*		*1940*		*10381*		*1942*
Discount rate – groups	***Model 3***		***Model 4***		***Model 3***		***Model 4***	
DR3 – 10mths (base)	–		–					
DR3 – 8mths	–0.361	(0.73)	0.874	(0.29)				
DR3 – 6mths	–0.495	(0.60)	0.940	(0.26)				
DR3 – 4mths	0.169	(0.67)	1.176	(0.36)				
DR3 – 2mths	0.369	(0.68)	1.482	(0.42)				
DR3 – 1mth	0.502	(0.72)	1.487	(0.44)				
DR3 – now	1.049	(0.71)	1.718	(0.50)				
DR3 –$500	1.585**	(0.48)	1.821**	(0.38)				
DR4 – $300 (base)					-		-	
DR4 – $310					–0.534	(0.67)	0.867	(0.23)
DR4 – $325					–0.521	(0.82)	1.112	(0.34)
DR4 – $350					–1.640**	(0.49)	0.520**	(0.13)
DR4 – $400					–0.468	(0.55)	0.972	(0.19)
DR4 – $500					–0.456	(0.48)	0.867	(0.16)
DR4 – $600					–0.306	(0.56)	0.928	(0.19)
DR4 – $800					–0.533	(0.63)	0.774	(0.21)
DR4 – $1000					–0.558	(0.66)	1.055	(0.24)
DR4 – $300 now					–1.082	(0.58)	0.755	(0.17)
R^2/Pseudo R^2		*0.0185*		*0.0118*		*0.0061*		*0.0055*
LL		*–5180*		*–954*		*–5178*		*–959*
AIC		*10376*		*1924*		*10377*		*1937*
BIC		*10419*		*1967*		*10430*		*1991*

*legend: * p<0.05; ** p<0.01; *** p<0.001*

The results from the unadjusted models demonstrate that respondents' indifference points had no association with BMI for time preference scenario 1, 2 or 4. The only significant result was the third time preference scenario for both the continuous measure of BMI and odds of being obese using both a continuous discount rate and the discount rate groups. The results from the continuous discount measure indicate a lower BMI (although very small effect, –0.0002) and reduced odds of being obese (although almost 1.00). Evaluating the discount rate groups may provide a better understanding of the association. Only the final option in scenario 3 was significant (in which respondents waited 12 months to pay $500 for the surgery) and respondents were more likely to be obese (odds ratio 1.82) with a 1.5 unit increase in BMI.

Based on these initial results, it is likely that other variables have a stronger association with BMI than the discount rate calculated in the models. Table 6.13 presents the models controlling for demographic and socioeconomic characteristics of the respondents (questions 1 and 2).

Table 6.13 Regression results: Time preference scenarios 1 & 2 (full model)

	DR1				DR2			
	BMI		Obese (OR)		BMI		Obese (OR)	
	β	SE	B	SE	β	SE	β	SE
	Model 5		*Model 6*		*Model 5*		*Model 6*	
Discount Rate 1	–0.026	(0.10)	0.994	(0.04)	0.267	(0.16)	0.983	(0.07)
Age								
25–34	1.23	(0.66)	1.254	(0.33)	1.249	(0.66)	1.250	(0.33)
35–44	1.015	(0.71)	1.032	(0.29)	1.033	(0.71)	1.028	(0.29)
45–54	2.942***	(0.71)	2.526**	(0.68)	3.024***	(0.71)	2.510*	(0.68)
55–64	2.596***	(0.74)	2.579**	(0.71)	2.691***	(0.74)	2.564*	(0.71)
65–74	2.060*	(0.84)	1.870	(0.61)	2.171**	(0.84)	1.855	(0.61)
75+	1.17	(0.91)	1.040	(0.43)	1.252	(0.91)	1.031	(0.43)
Male dummy	–0.047	(0.31)	0.777*	(0.10)	-0.083	(0.31)	0.780	(0.10)
Education								
Certificate/Diploma	0.378	(0.37)	1.099	(0.16)	0.396	(0.37)	1.098	(0.16)
Bachelors/graduate degree	–0.978**	(0.37)	0.654**	(0.11)	-1.010**	(0.37)	0.656**	(0.11)
Marital status								
Married/living together	0.663	(0.40)	0.984	(0.16)	0.637	(0.40)	0.985	(0.16)
Divorced/sep/widowed	0.614	(0.54)	1.056	(0.22)	0.568	(0.54)	1.057	(0.22)
Income								
\$20,000–\$79,999	–0.013	(0.67)	1.267	(0.31)	0.08	(0.67)	1.265	(0.31)
\$80,000–\$149,00	–0.421	(0.69)	1.253	(0.34)	-0.33	(0.69)	1.255	(0.33)
\$150,000+	–0.305	(0.77)	1.352	(0.43)	-0.197	(0.77)	1.349	(0.43)
Don't know/prefer not to	–0.165	(0.73)	1.292	(0.35)	-0.068	(0.73)	1.289	(0.35)
Work status								
Retired	0.281	(0.50)	0.963	(0.20)	0.313	(0.50)	0.961	(0.20)
Disabled/sick/unpaidwork	2.575**	(0.99)	2.038*	(0.59)	2.553**	(0.99)	2.040*	(0.59)
Studying	–0.026	(0.80)	1.142	(0.36)	-0.021	(0.80)	1.142	(0.36)
Unemployed	1.218*	(0.55)	1.372	(0.25)	1.227*	(0.55)	1.372	(0.25)
Other	2.615	(1.44)	2.138	(0.98)	2.634	(1.44)	2.138	(0.98)
Smoker	–1.238***	(0.35)	0.677*	(0.11)	-1.319***	(0.35)	0.678*	(0.11)
Drinker	0.531	(0.33)	1.257	(0.18)	0.565	(0.33)	1.256	(0.18)
No medical condition	–1.704***	(0.30)	0.535***	(0.07)	-1.699***	(0.30)	0.534***	(0.07)
Activity								
Less than once a week	–0.445	(0.59)	0.734	(0.15)	-0.384	(0.59)	0.733	(0.15)
1–2 time a week	–0.770	(0.53)	0.568**	(0.11)	-0.717	(0.53)	0.567*	(0.11)
3–6 times a week	–1.478**	(0.52)	0.494***	(0.10)	-1.394**	(0.52)	0.493***	(0.10)
Every day	–1.901***	(0.52)	0.449***	(0.10)	-1.827***	(0.52)	0.447***	(0.10)
Constant	26.952***	(0.55)	0.432*	(0.16)	26.654***	(0.55)	0.435*	(0.16)
R^2/Pseudo R^2		*0.117*		*0.0782*		*0.118*		*0.0782*
Log-likelihood		*–5094*		*–890*		*–5093*		*–890*
AIC		*10246*		*1837*		*10244*		*1837*
BIC		*10402*		*1993*		*10400*		*1994*

*legend: * p<0.05; ** p<0.01; *** p<0.001*

Table 6.14 presents the models controlling for demographic and socioeconomic characteristics of the respondents for time preference scenarios 3 and 4.

Table 6.14 Regression results: Time preference scenario 3 & 4 (full model)

	DR3				DR4			
	BMI		Obese (OR)		BMI		Obese (OR)	
	β	SE	β	SE	B	SE	B	SE
	Model 5		*Model 6*		*Model 5*		*Model 6*	
Discount Rate 1	0.000	(0.00)	1.000	(0.52)	-0.031	(0.07)	1.003	(0.03)
Age								
25–34	1.22	(0.66)	1.252	(0.32)	1.251	(0.66)	1.254	(0.33)
35–44	1.009	(0.71)	1.029	(0.29)	1.007	(0.71)	1.030	(0.29)
45–54	2.940***	(0.71)	2.515*	(0.68)	2.959***	(0.71)	2.517*	(0.68)
55–64	2.599***	(0.74)	2.566*	(0.71)	2.610***	(0.74)	2.574*	(0.71)
65–74	2.062*	(0.84)	1.857	(0.61)	2.072*	(0.84)	1.865	(0.61)
75+	1.163	(0.91)	1.031	(0.43)	1.210	(0.91)	1.050	(0.44)
Male dummy	–0.045	(0.31)	0.779	(0.09)	-0.040	(0.31)	0.778	(0.10)
Education								
Certificate/Diploma	0.381	(0.37)	1.090	(0.15)	0.375	(0.37)	1.101	(0.16)
Bachelors/graduate degree	–0.975**	(0.37)	0.658**	(0.11)	-0.963**	(0.37)	0.658**	(0.11)
Marital status								
Married/living together	0.66	(0.40)	0.978	(0.15)	0.628	(0.40)	0.983	(0.16)
Divorced/sep/widowed	0.607	(0.54)	1.052	(0.22)	0.585	(0.54)	1.052	0.22)
Income								
$20,000–$79,999	0.006	(0.67)	1.263	(0.30)	0.009	(0.67)	1.271	(0.31)
$80,000–$149,00	–0.392	(0.69)	1.262	(0.33)	-0.368	(0.69)	1.260	(0.33)
$150,000+	–0.283	(0.77)	1.355	(0.43)	-0.279	(0.77)	1.358	(0.43)
Don’t know/prefer not to	–0.149	(0.73)	1.291	(0.35)	-0.149	(0.73)	1.294	(0.35)
Work status								
Retired	0.279	(0.50)	0.965	(0.21)	0.289	(0.50)	0.964	(0.20)
Disabled/sick/unpaidwork	2.578**	(0.99)	2.019*	(0.58)	2.593**	(0.99)	2.036*	(0.59)
Studying	–0.029	(0.80)	1.151	(0.36)	-0.025	(0.80)	1.138	(0.36)
Unemployed	1.220*	(0.55)	1.373	(0.25)	1.234*	(0.55)	1.370	(0.25)
Other	2.618	(1.44)	2.130	(0.97)	2.623	(1.44)	2.140	(0.98)
Smoker	–1.249***	(0.35)	0.678*	(0.10)	-1.251***	(0.35)	0.674*	(0.10)
Drinker	0.537	(0.33)	1.249	(0.18)	0.557	(0.33)	1.257	(0.18)
No medical condition	–1.709***	(0.30)	0.538***	(0.07)	-1.709***	(0.30)	0.536***	(0.07)
Activity								
Less than once a week	–0.44	(0.59)	0.724	(0.15)	-0.409	(0.59)	0.739	(0.15)
1–2 time a week	–0.764	(0.53)	0.562*	(0.11)	-0.768	(0.53)	0.569*	(0.11)
3–6 times a week	–1.471**	(0.52)	0.489***	(0.09)	-1.478**	(0.52)	0.495***	(0.10)
Every day	–1.903***	(0.52)	0.444***	(0.09)	-1.924***	(0.52)	0.451***	(0.10)
Constant	26.904***	(0.55)	0.446*	(0.16)	26.927***	(0.55)	0.426*	(0.16)
R^2/Pseudo R^2		*0.117*		*0.0786*		*0.117*		*0.0776*
Log-likelihood		*–5094*		*–889*		*–5083*		*–889*
AIC		*10246*		*1837*		*10223*		*1836*
BIC		*10403*		*1993*		*10379*		*1992*

*legend: * p<0.05; ** p<0.01; *** p<0.001*

In all models, after adjusting for demographic and socioeconomic characteristics of the respondents, there were no significant impacts of the estimated discount rates, by BMI or the probability of being obese. The largest association was for those aged 45–64 and those respondents who reported being sick, disabled or in unpaid work. The characteristics that had a negative effect on BMI or reduced the odds of being obese were those with a higher education, smokers, and respondents with higher levels of activity.

The regression results for the adjusted models with discount groups for each of the time preference scenarios had similar results to the models using the continuous discounting estimates, with the same significant characteristics impacting the weight variables. Figure 6.7 presents the predicted probabilities of being obese for each of the questions for the time preference scenarios, comparing the adjusted and unadjusted models. Overall, the differences in the discount rates in each time preference scenario had little impact on the probability of being obese. Only the last option in the third time preference scenario was significant in the unadjusted model but, once adjusted for other covariates, it also became insignificant. Also, looking at the overall trend of the four time preference scenarios, only the third scenario displayed a trend, with an increased probability (although insignificant) of being obese as the months of waiting for surgery decreased.

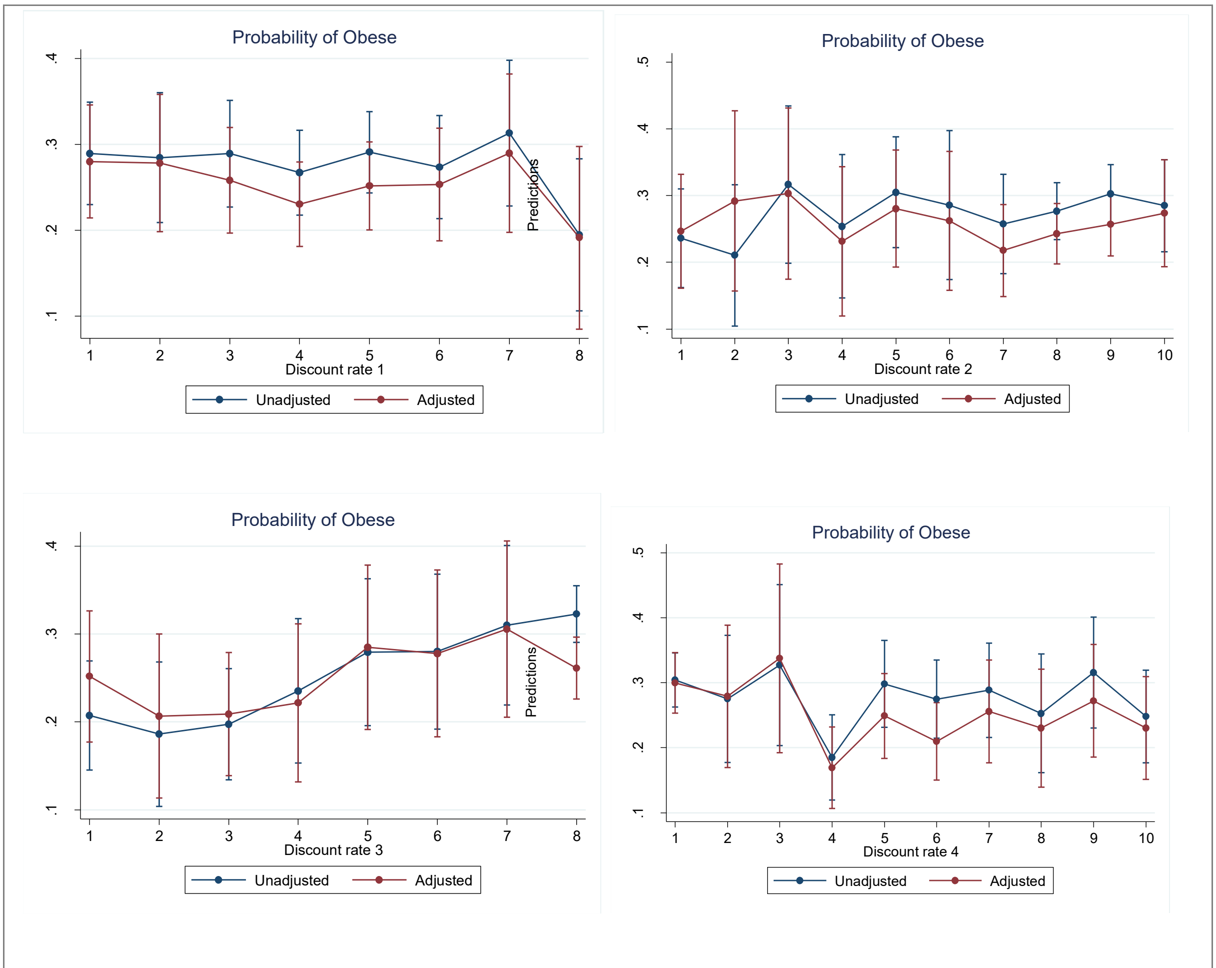

Figure 6.7 Probability of being obese by discount rate groups (questions 1, 2, 3 & 4) (unadjusted vs adjusted)

The literature presented three important behavioural aspects of time preferences with respect to obesity: impatience, hyperbolic discounting and sign effect (Ikeda et al., 2010). Overall, the results from this chapter did not demonstrate evidence for impatience, as there were no differences in the discount rates between overweight and obese individuals. In fact, the third time preference scenario, asking respondents to pay for a surgical operation, resulted in a significantly greater proportion of obese individuals waiting 12 months for the surgery. However, this result may indicate that individuals discount health and money differently. The evidence for hyperbolic discounting could not be evaluated with the time preference questions asked, as the first two questions did not vary the time for the reward (or penalty) to determine whether overweight or obese individuals discount the immediate future more than the distant future.

There was some evidence of the sign effect in the data; however, the data from the first and second time preference scenarios did not match exactly in terms of the calculated discount rates. Nevertheless, by comparing the proportion of respondents with indifference points between 10% and 100% from the first scenario with the proportion of respondents with indifference points between 10% and 125% from the second scenario, the sign effect was evident. Only 26% of respondents who had discount rates in the range of 10–100% from the first scenario had discount rates between 10–125% in the second scenario, with the majority (63%) of these respondents reporting a discount rate lower than 10% in the second scenario. This indicates that respondents discount future negative losses at a lower rate than future positive gains.

6.6.6 Sensitivity analysis

The results from the sensitivity analyses are presented in Table 6.15. The analyses displayed use the continuous discount rate from the first time-preference scenario and BMI as the dependent variable, as the sensitivity analyses with the other three discount rates resulted in similar conclusions. The first sensitivity analysis (SA1) excluded respondents who chose one option for all four scenarios. The second analysis (SA2) excluded respondents who failed the dominant DCE choice task. The third analysis (SA3) excluded respondents who finished the entire survey in under 3 minutes and 45 seconds and the final analysis (SA4) excluded respondents who were highlighted as being a bad fit during the regression diagnostics.

Table 6.15 Time preference sensitivity analyses

	SA 1	SA 2	SA 3	SA 4
	N = 1611	N = 1387	N = 1605	N = 1529
Discount Rate 1	–0.001	–0.008	–0.015	–0.081
Age				
25–34	0.919	0.892	0.979	1.203*
35–44	0.709	0.712	0.613	0.69
45–54	2.387***	2.475**	2.385***	2.961***
55–64	2.083**	2.205**	2.073**	2.357***
65–74	1.826*	2.221*	1.829*	2.124**
75+	0.774	1.124	0.822	0.87
Male dummy	–0.168	–0.201	–0.151	0.622*
Education				
Certificate/Diploma	0.604	0.512	0.598	0.696*
Bachelors/graduate degree	–0.725*	–0.857*	–0.768*	–0.624*
Marital status				
Married/living together	0.813*	0.756	0.780*	0.944**
Divorced/sep/widowed	0.749	0.888	0.663	1.301**
Income				
\$20,000–\$79,999	0.104	0.11	0.111	0.271
\$80,000–\$149,00	–0.062	0.122	–0.067	0.251
\$150,000+	0.106	0.104	0.126	0.649
Don’t know/prefer not to	0.15	–0.104	0.072	0.161
Work status				
Retired	0.054	–0.24	0.015	0.071
Disabled/sick/unpaid work	1.601	1.077	1.419	1.21
Studying	0.115	0.135	0.1	0.342
Unemployed	0.839	1.066	0.854	0.686
Other	2.131	2.058	2.123	1.692*
Smoker	–1.429***	–1.573***	–1.396***	–0.958**
Drinker	0.394	0.361	0.433	0.524
No medical condition	–1.412	–0.822	–1.428	–1.725*
Activity				
Less than once a week	–0.406	–0.266	–0.215	–0.098
1–2 times a week	–0.426	–0.467	–0.31	–0.406
3–6 times a week	–0.919	–0.708	–0.777	–0.781
Every day	–1.126*	–1.015	–1.062	–1.063*
Constant	23.810***	23.646***	23.728***	22.484***
R^2/Pseudo R^2	0.175	0.176	0.174	0.236
Adjusted R2	0.156	0.154	0.155	0.218
Log-likelihood	–4993	–4293	–4979	–4428
AIC	10060	8659	10031	8929

legend: * p<0.05; ** p<0.01; *** p<0.001

The sensitivity analyses were similar for the other three time preference scenarios, other than a positive coefficient on the discount rate for the second scenario in the second sensitivity analysis. When taking out those respondents who failed the DCE dominance check, the coefficient was greater, indicating an increased association with BMI. These outliers were more likely to be female, drink alcohol and unemployed/unpaid work. However, looking at the groups for this sensitivity analysis it appears that low numbers in some of the groups are driving this result.

Overall, being a smoker, having a medical condition and high levels of activity are associated with lower BMI. The association of increased BMI was found for those aged 45–64 and sick, disabled or in unpaid work – similar results to the full analyses presented.

6.6.7 Public policy questions

All respondents who answered the public policy questions were included in the statistical summary; resulting in 1,863 total respondents.[58] Overall, respondents had similar opinions with regards to public policy towards obesity. Table 6.16 summarises the proportion of respondents who answered each of the public policy questions, separated by normal weight, overweight and obese respondents.

Table 6.16 Respondent public policy opinions by BMI

Characteristic	All	Normal weight	Overweight	Obese	P-value for χ^2
Respondents	**N = 1863**	**N = 723**	**N = 616**	**N = 524**	
Obesity problem					*0.087*
Extreme problem	25.8%	27.4%	22.6%	27.5%	
Severe problem	41.7%	40.4%	44.0%	40.6%	
Moderate problem	25.2%	24.8%	24.7%	26.3%	
Slight problem	3.4%	2.6%	4.4%	3.2%	
Not a problem	4.0%	4.8%	4.4%	2.3%	
Role government should play in reducing obesity					*0.073*
No role	12.0%	11.3%	14.4%	10.1%	
Minor role	45.0%	43.2%	45.9%	46.6%	
Major role	42.9%	45.5%	39.6%	43.3%	
Should the government pay individuals who are overweight/obese to lose weight?					***<0.001***
Yes	28.6%	21.9%	26.9%	39.9%	
No	71.4%	78.1%	73.1%	60.1%	
Should the government tax unhealthy food/drink?					*0.239*
Yes	59.7%	60.4%	61.4%	56.7%	
No	40.3%	39.6%	38.6%	43.3%	

The majority of respondents thought obesity was a severe/extreme problem (68%), with 42.9% believing the government should play a major role in reducing obesity. The only statistically significant difference by BMI group was concerning opinions on whether the government should pay individuals to lose weight. A larger proportion of obese respondents (39.9%) thought that the government should pay people to lose weight compared to the overweight and

58 The total sample (N=1863) is greater than the sample for the time preference questions (N=1,627), as some respondents failed to finish the survey between the public policy questions (which came earlier in the survey) and the time preference questions included at the end of the survey.

normal weight individuals (26.9% and 21.9%). Similarly, obese respondents were less in favour of a tax on unhealthy food and drink, however this finding was not significant. The differences in opinions between genders was also evaluated (Table 6.17).

Table 6.17 Respondent public policy opinions by gender

Characteristic	All	Males	Females	P-value for χ^2
Respondents	**N = 1863**	**N = 984**	**N = 879**	
Obesity problem				***<0.001***
Extreme problem	25.8%	22.1%	30.0%	
Severe problem	41.7%	42.0%	41.3%	
Moderate problem	25.2%	26.6%	23.5%	
Slight problem	3.4%	3.7%	3.1%	
Not a problem	4.0%	5.7%	2.0%	
Role government should play in reducing obesity				***<0.001***
No role	12.0%	14.9%	8.8%	
Minor role	45.0%	43.5%	46.8%	
Major role	42.9%	41.6%	44.5%	
Should the government pay individuals who are overweight/obese to lose weight?				***0.016***
Yes	28.6%	26.2%	31.3%	
No	71.4%	73.8%	68.7%	
Should the government tax unhealthy food/drink?				*0.825*
Yes	59.7%	59.5%	60.0%	
No	40.3%	40.5%	40.0%	

The opinions of the respondents with regards to public policy were more different than between the BMI groups. A larger proportion of males thought that the government should not play a role in reducing obesity (14.9% vs 8.8%). Females viewed obesity as a more extreme problem than males (30.0% vs 22.1%) with a larger proportion of female respondents saying the government should pay individuals to lose weight. With regards to taxes, 60% of respondents thought the government should tax unhealthy food and drink (regardless of weight status or gender). In general, female respondents were more approving of government intervention and obese respondents were more in favour of financial incentives to lose weight.

6.7 Discussion

The *a priori* expectation of the chapter was that obese people would have different discount rates compared to non-obese people, as obese individuals may not consider the long-term consequences of their lifestyle choices. The results from the four time preference elicitation scenarios comparing normal weight, overweight and obese respondents, only demonstrated significant differences in the scenario that was specifically related to a health benefit, with obese respondents preferring to wait for surgery and pay a lower amount. This finding supports the theory that obese individuals may discount health benefits and monetary benefits differently.

The analyses using BMI or the probability of being obese as the outcome measure did not find any significant impacts of the respondents' calculated discount rate on these weight variables, except for the third scenario (the health benefit question). After controlling for sociodemographic and economic variables, this association failed to be significant. Overall, there was a larger effect of time preferences in models using a binary measure of obesity as opposed to using BMI as a continuous measure; a result also found by Gray (2011). The probability of being obese was mostly impacted by age, specifically respondents aged 45–64. In general, the results did not show strong evidence of the impact of time preferences on the measure of body mass. It is possible that a third variable may be the cause of this association, which is independent of obesity. Factors such as impulsivity may have a mediating effect on this relationship.

Clearly more research is needed to explore the relationship between the rate of time preference and obesity, and possible policies to targeting the marginal rate of time preference, if evidence of a link is supported. If time preferences do impact on weight, policies that incentivise people to adopt healthier lifestyles may be successful. At a rudimentary level, teaching children to save money in a piggy bank is one way of encouraging patience (Zhang & Rashad, 2008). Furthermore, policies that reduce the marginal rate of time preferences are needed, such as those that raise the cost of choices people make in the present that could lead to obesity or those that address self-control issues and 'nudge' people to make the right decisions. It is important to find solutions that address the behavioural problems that exist in overweight/obesity and design policies that address impulsive food decisions. Based on previous research, this would be the recommended solution; however, given the association between higher time preferences and obesity is unclear, other research areas may need to be explored, such as monetary incentives to drive change of unhealthy behaviours.

Interestingly, other studies have found that discount rates for food are higher than for money (Odum et al., 2006; Odum & Rainaud, 2003) or other outcomes (such as books and music) (Charlton & Fantino, 2008). Rasmussen et al. (2010), and a later study by Hendrickson and Rasmussen (2012), found that high body fat percentage predicted discounting for food-related outcomes but not monetary outcomes. The theory is that food is discounted more heavily as it is a ‘primary reinforcer’. Another study demonstrated that overweight and obese individuals with higher discount rates consume a greater number of calories when dining out (Appelhans et al., 2012). This differs from other studies which find monetary discounting differences between obese and normal weight individuals (Weller et al., 2008; Fields et al., 2011). The use of measured body fat percentage compared to BMI may explain the different findings. This chapter did not assess any choices around food; however, there were differences between the discounting of the monetary questions compared to the health-related questions, which may be driven by similar mechanisms to choices around food. Lazaro et al. (2002) found that people discount health outcomes at a higher rate than monetary outcomes. Becker and Mulligan (1997) argue that differences in time preferences are caused by differences in health, but not the inverse.

Previous research has demonstrated that those with higher incomes and executive functions (such as inhibitions, working memory and mental flexibility) had higher scores for the consideration for the future scales (CFCS) (a 12-item scale to represent how much individuals focus on future needs and concerns) and overall their preference was to wait for rewards. The methods employed in this chapter assumed that there is no reverse causality from BMI to time preferences. Future analyses could focus on methods that control for the endogeneity of time preferences, as there may be similar issues for obesity and time preferences with unobservable factors simultaneously affecting both.

6.7.1 Strengths and limitations

There exist some concerns with the scenario used to calculate the discount rates in the monetary questions. The discount rates between the reward and penalty questions were not comparable, which would have been beneficial for estimating evidence of the sign effect. The health time preference question may have used an immediate amount that was too high compared to the future trade off amount ($2000 vs $500) given the short time period (less than a year) of the operation. Furthermore, with all stated preference data, all questions were hypothetical and may not reflect how the respondents would behave if these actual scenarios were presented to respondents. The survey also did not ask respondents if they had children and could not be controlled for in the model. It is possible the having children could impact how people perceive the future and make different choices when faced with trade-offs. Other time preference questions could have been useful to collect, to use as a proxy for time period preferences to compare with other studies.

Ikeda et al. (2010), for example, asked participants questions such as '*When you go out, how high a probability of rainfall makes you bring an umbrella with you*?' to assess risk aversion and '*When did you do homework assignments in the summer vacation in your high school days?*' to assess procrastination. There are, however, drawbacks to using proxies for time preference behaviour. As Borghans and Galsteyn (2006) demonstrated, not all measures of time preference are associated with increases in BMI or obesity, as only two of the 11 items of the CFCS were significantly associated with BMI. The authors concluded that other intertemporal factors impact BMI, such as factors that regulate current and future health and well-being. A major shortcoming in all the analyses was the absence of any dynamic variables that could be influencing BMI over time, such as technological changes in food, increase in convenience foods and food prices. Additionally, variables such as taxation and subsidies for savings that could directly impact the proxies used for time preferences were not captured in the analysis.

Future studies could take advantage of the Barratt Impulsiveness scale (BIS-11), which may be a better correlate of time preferences with respect to obesity. The BIS-11 questionnaire includes 30 items to assess personality/behavioural aspects of impulsiveness, including attention, motor self-control, cognitive complexity, perseverance, cognitive instability and non-planning.[59] Other probability tests, such as the standard gamble, could also be used to determine participants' willingness to trade off health for particular lifestyle changes. Future work that explores the lack of willpower or self-control may be beneficial. For example, Zhang and Rashad (2008) suggest that creating incentives that address the issue of lack of self-control, such as using pre-commitment devices, may be effective in reducing obesity.

One of the strengths of the analysis was the inclusion of the weight-loss interventions question. This question provided some interesting insights into the value individuals placed on losing weight, with almost a third of respondents willing to accept the same reward in six months conditional on losing weight. This lends support for policies that 'nudge' people to make the right decisions and address the issue of self-control.

6.7.2 Conclusions

The results from the time preference survey questions did not support the hypothesis that there are significantly different rates of time preferences between obese and normal weight individuals. Once age, smoking status, activity levels and the presence of a long-term health

[59] Barratt Impulsiveness Scale: http://www.impulsivity.org/measurement/bis11

condition were controlled for, the effect on BMI was not significant. The only differences between the discount rates for the weight categories was for the health scenario, in which obese individuals were less willing to pay more for an earlier operation. This may indicate that obese individuals discount health and money differently. The endogeneity issue between rates of time preferences, health and weight is an area that deserves more attention. If research can find more evidence that increases in the rate of time preferences have contributed the increase in obesity, policies that raise cost of choices made in the here and now that lead to obesity may be beneficial. Moreover, policies that address self-control issues and help ‘nudge’ individuals to make different decisions with regards to their health may be one solution to aid in reducing obesity. It is important to find solutions that address the behavioural problems that exist in overweight/obese people and design policies that address these impulsive food decisions.

7 DISCUSSION

This thesis has used an economics perspective to investigate interventions for individuals aimed at reducing obesity. Specifically, the research undertaken for this thesis aimed to provide insights into issues of conducting economic evaluations of obesity interventions, the relationship between quality of life (QoL) and weight change and consumer preferences for weight-loss programs. The association between obesity and QoL was further explored using a secondary analysis aimed at disentangling the existing endogeneity. Data from the Household Income and Labour Dynamics Australia (HILDA) survey was used in combination with an online consumer survey developed during the research. The survey included a discrete choice experiment (DCE), time preference study, and sociodemographic and attitudinal questions; over 1,800 respondents completed the survey. The aim of the DCE was to understand consumer preferences for weight-loss interventions and the time preference study estimated the rate of time preferences for future money and health outcomes. Differences between obese and normal weight individuals were explored.

7.1 What I did

Despite a large amount of funding made available to tackle obesity, rates continue to rise. A review of current cost-effectiveness analyses of obesity interventions in adults was conducted to assess and critique the current modelling methods. Chapter 2 demonstrated that while the results of economic evaluations show that most interventions are cost-effective, claims of cost-effectiveness are complicated by inadequate documentation of methodology and questionable modelling. The review highlighted issues such as how QoL (in particular, changes in QoL following weight loss) is modelled; the implications are that the resulting ICERs are likely to be over stating the cost-effectiveness of interventions (i.e., reporting a lower ICER than would be expected). Many published evaluations did not provide sufficient detail on how QoL values were applied and/or how secondary sources were used to generate utility values (in many cases these sources could not be verified), which further adds uncertainty to the claims of cost-effectiveness. Many modelling approaches used utility values derived from cross-sectional data, which inherently assumes that weight loss leads to gains in QoL. This contradicts the current evidence from longitudinal studies that show little or weak association between weight loss and

QoL gain (Warkentin et al., 2014a). The review conducted in Chapter 2 adds to the literature by providing a picture of the current evidence from cost-utility analyses of behavioural interventions, including highlighting issues in the modelling of QoL.

The source of funding for economic evaluations appears to influence the results; evaluations funded by pharmaceutical companies generally produced more favourable results. The implications are that governments may be spending scarce resources on interventions that will not produce the expected benefits, particularly in terms of improvements in QoL.

Most of the economic evaluations reviewed in Chapter 2 incorporated distinct monotonic utility values by health state, usually represented by body mass index (BMI) category (e.g., normal, overweight, obese and severely obese). This modelling approach assumes that individuals gain QoL when weight is lost, since the individual moves to a healthy BMI category (e.g., obese to overweight). This finding motivated the analyses conducted in Chapter 3, which investigated the relationship between QoL and obesity using data from the HILDA survey. The cross-sectional analysis supported the results of previous studies, showing that obese individuals have a lower QoL than normal weight individuals. The analysis exploited the panel nature of the data and provided a longer perspective, showing that reductions in body weight do not necessarily correspond to increases in health-related QoL. Furthermore, in terms of yearly weight changes (as modelled in economic evaluations) only remaining severely obese or becoming severely obese resulted in significant decrements in QoL. These results are congruent with the literature, demonstrating that while QoL decreases with weight gain, it does not improve with weight loss (Laxy et al., 2014). These results imply that current models assessing the cost-effectiveness of weight-loss interventions that use QoL as the main outcome measure may be overstating gains in QoL due to weight loss. Many of the current longitudinal studies provided results in terms of QoL and not utility values. The use of the SF-6D score (derived from the SF-36 health-related QoL questionnaire) as the outcome measure in the analysis provided a direct estimate of utility to compare to the values used in other economic evaluations.

Reviews of the literature have demonstrated that weight loss is associated with higher gains in the physical aspects of QoL rather than the mental aspects (Kroes et al., 2016). Using the mental health and physical health summary scores from the SF-36, my analysis supported these findings. The aim of the research reported in Chapter 4 was to explore whether underlying conditions (such as depression) persist after weight loss. Studies have found that weight loss treatments do not significantly improve depressive symptoms (Maciejewski et al., 2005). Using the HILDA survey, variables were created that identified individuals as having a diagnosis of depression and/or experiencing a stressful life event (such as injury, death of family member, being a victim of violence, being made redundant). Given the presence of reverse causality between QoL and obesity, an instrumental variable approach was employed, with stressful life events used as an instrument and two-stage models estimated. The results suggested that the effect of QoL on obesity may be the result of poorer mental health. All the stressful life events were associated with decrements to mental health (identified by both the mental component summary (MCS) measure and the mental health dimension (MH) of the SF-36). The results from the two-stage model indicated that the QoL model resulted in a greater propensity to be obese when compared to the two-stage model for depression, reinforcing the view that underlying depression may persist, negatively affecting QoL, even after a significant weight loss. The implications of these results are that it is important to identify persons with poorer QoL (especially those with poor mental health) as being at higher risk of future weight gain. This finding supports the work of Cameron et al. (2012) which stated that ‘a focus on health-related QoL may be beneficial in weight management strategies’.

Weight-loss programs inherently focus on weight loss as the primary outcome/goal. However, the findings of Chapters 3 and 4, that weight loss may not be associated with significant improvements in QoL, leads to the question of how important QoL improvements (particularly in the short term) are to the success of a weight-loss program. Chapter 5 attempted to understand what attributes of weight-loss programs people are most interested in and whether the preferences of obese individuals are different to normal weight individuals. A discrete choice experiment was developed to explore these issues, with the attributes and levels determined from a literature review and focus group. An online panel was used to recruit more than 1,800 respondents, representative of the Australian population, to elicit the preferences between two hypothetical weight-loss programs. As expected, lower-cost interventions and those which included an individually tailored exercise program were preferred. Surprisingly, programs that led to an improvement in respondents’ QoL were preferred over ones that produced weight loss. This result reinforces the need for a greater focus to be placed on the QoL outcomes of obesity interventions. The analysis also demonstrated that respondents were reluctant to enrol in weight-loss programs. One-quarter of respondents always chose not to enrol in the program; these respondents were more likely to be men, overweight, older and satisfied with their current weight. This finding suggests that individuals do not fully understand the implications of higher body weight or that larger incentives may be necessary to entice these individuals to adopt healthier lifestyles. This may also represent a subset of the population who do not wish to change their current lifestyle (or the health risks associated with their lifestyle) and interventions aimed at these people will prove difficult.

The final chapter of the thesis explored whether obese individuals have preferences which are more focused on the present – in other words, a different rate of time preference – which has been suggested as one of the causes of obesity (Lakdawalla & Philipson, 2009). The policy implication is that interventions may need to be designed that provide incentives for those with present-oriented time preferences, which in turn may reduce the prevalence of obesity. An analysis of the rate of time preferences was incorporated in the online survey described in Chapter 5. The first scenario elicited preferences using a monetary reward question, the second scenario used a monetary penalty, the third scenario elicited respondents' preferences for a future health-related benefit and the final scenario elicited preferences for a weight-loss intervention. The results suggest that there are no significant differences in the rate of time preferences between normal weight and obese individuals. Furthermore, there was little evidence of differences in discounting between respondents in different weight categories. One significant result was that obese individuals were less willing to pay for an earlier operation than overweight and normal weight individuals. Using operation waiting times as a proxy for health benefits, 57% of obese respondents chose to pay $500 and wait 12 months rather than paying $2,000 for an earlier operation. This implies that obese individuals potentially discount health and money differently, compared to normal weight individuals.

An interesting extension of this work was highlighted in the final time preference scenario. The first choice-task involved a choice between receiving $300 now to enrol in weight-loss program or waiting six months and receiving $300, conditional upon losing five kilograms. Although the reward was the same, almost a third of respondents chose to wait six months, implying that interventions that offer a 'nudge' to commit to healthier lifestyles may be more successful. Overall, further research is warranted to explore whether there are differences in how people discount money compared to health and what incentives would influence individuals to adopt and commit to healthier lifestyles.

7.2 Limitations and Challenges

An overall challenge faced in each chapter in this thesis was the amount of previous research related to obesity and obesity-related diseases/outcomes. The literature review process resulted in thousands of relevant articles. After reading and reviewing these articles, more articles of relevance were highlighted. Furthermore, given the aetiology of obesity, with a multitude of concurrent influences (both internal and external) and no single cause, it is difficult to isolate particular economic factors for analysis. This thesis concentrated on the areas where economists have recommended obesity research should focus – in particular, assessing the cost-effectiveness of programs and policies, understanding the factors that contribute to obesity, and researching the optimal design of incentives for weight loss (Cawley, 2015). In combination, the overall results of this thesis contribute to this literature.

An overarching limitation in understanding obesity from an economic perspective is the rigour with which economic modelling of interventions is conducted, which, in turn, has implications for interpretation of the results and consequent policy implications. This thesis has demonstrated that there are major empirical issues in terms of the modelling inputs used in economic evaluations of obesity interventions, specifically in relation to QoL values, which result in erroneous conclusions concerning the overall benefit and cost-effectiveness of interventions. An area for future investigation is obtaining QoL values for economic evaluation that reflect the true nature of the association between obesity and QoL. Utility values that are transferrable across platforms and validated through formal statistical methods will ensure that future economic models are able to accurately predict which interventions represent 'best value for money'. Moreover, due diligence is needed when comparing results from models that apply QoL values by BMI states compared to models that apply QoL values by disease outcomes. Much of the literature reporting QoL has used data from cross-sectional studies or from RCTs in specific populations. Although there is weak evidence for a relationship, cost-effectiveness studies continue to use models that directly evaluate weight loss and the resulting impact on QALYs. There are questions about whether this is appropriate, especially for models being applied to a general population

The panel data sourced from the longitudinal HILDA study and used throughout the thesis, provided a rich dataset to analyse changes in weight over time. However, modelling fluctuations in weight is problematic, as weight loss and gain follow numerous patterns. The majority of analyses used one-year change in weight to measure associated changes in QoL, which may have underestimated the impact of weight changes on QoL. Furthermore, inherent to all statistical models, there is always a risk that the models are not specified correctly and suffer from various sources of bias. Another limitation is the problem of differentiating between intentional and unintentional weight loss, either due to disease or non-disease related reasons (although health-status was controlled for in the models).

The utility instrument used in the HILDA survey (SF-36) differed from the instrument included in the DCE (EQ-5D), which may impact the comparability of results across chapters. Using different instruments was a pragmatic choice, since the EQ-5D was more readily transferable to the DCE setting. Previous research has demonstrated similarities between patterns of QoL against BMI, using either instruments (Dixon et al., 2004), therefore it is unlikely that the use of different utility instrument would materially impact the final conclusions.

Another challenge inherent to all of the empirical chapters was the use of a general population to make inferences. Although respondents to both the HILDA survey and the online panel from Pureprofile were representative of the Australian population, the motivation of obese individuals trying to lose weight, compared to similar people not trying to lose weight, may differ. Additionally, the gain in QoL may be overstated in the DCE, as these values were sourced from cross-sectional data and some of the weight loss scenarios presented in the vignettes may have demonstrated major gains in QoL (such as moving from 0.60 to full health), which may not occur from weight loss (as highlighted in Chapter 3).

A number of limitations were identified during the construction of the DCE, which impeded the timeliness of data collection. The survey construction was conducted directly in Survey Engine without any user support because Survey Engine provided a free student license to help them develop their survey platform. Detailed feedback to Survey Engine was provided as part of this agreement. Although this process was an immense learning opportunity, it required a substantial time commitment, especially as it involved multiple pilots and testing of the survey. A strength of the DCE and a novel aspect of the design was the use of QoL in the DCE. This was an innovative approach, as current DCEs tend to focus on more obvious outcomes concerning obesity, such as weight loss (in kilograms), weight change, risk reduction in comorbidities or changes to diet and physical activity. Although clinical trials often collect QoL data, obesity interventions usually focus on weight loss and reduction of comorbidities as the primary outcomes. This may indicate a discrepancy between the primary aims in a trial and what attributes of a weight-loss program overweight individuals prefer.

7.2.1 Normal weight versus obese

Many differences between normal weight and obese individuals were highlighted throughout the research. Most significantly, obese individuals have significantly lower levels of QoL than normal weight individuals. Additionally, obese individuals scored lower on all eight dimensions of QoL in the SF-36, with severely obese individuals having even lower QoL scores. Compared to normal weight individuals who remained normal weight, becoming severely obese or remaining severely obese was associated with decrements in QoL for males. For females, the results were even more pronounced, with any movement to obese/severely obese causing decrements to QoL. Furthermore, remaining obese appears to affect the physical rather than the mental health aspects of QoL.

Further differences between obese and normal weight individuals were observed when depression was investigated; obese respondents reported a higher prevalence of depression. Based on the SF-36 MCS summary scores and the mental health dimension, individuals who were severely obese were the most likely to be depressed. Obese individuals appear to experience a greater number of stressful life events compared to those who are not obese.

Normal weight and obese respondents also have different preferences for weight-loss programs. Compared to normal weight respondents, obese respondents preferred programs which promised higher weight loss (a predictable result) and programs that included individual exercise programs. Obese individuals had a clear preference for programs that required no exercise, which was the least preferred type of program for normal weight respondents. This further emphasises the need to consider the preferences of obese people when weight-loss programs are designed. Interestingly, respondents who were overweight but considered their weight acceptable had similar preferences to normal weight individuals. This may indicate that overweight individuals may not fully understand the health risks associated with high body weight or, as previously mentioned, are content to remain overweight This may be because being overweight is considered the new norm.

Although overall no significant association was observed between obesity and the rate of time preferences, the responses of obese individuals to the health question (knee surgery) differed from overweight and normal weight individuals (as discussed above). Additionally, responses to the public policy questions suggest that a significantly higher proportion of obese individuals believe the government should pay people to lose weight.

7.2.2 Quality of life

An ongoing theme of this thesis has been the importance of the QoL of overweight and obese individuals. The literature review in Chapter 2 demonstrated that QoL is poorly modelled in economic evaluations. It was shown in Chapter 3 that QoL does not improve with weight loss, especially in the short term. The results reported in Chapter 4 demonstrated that the mental health aspects of QoL persist even if weight is lost. The results from the DCE showed that QoL outcomes are especially important when choosing a weight-loss program. Finally, the results reported in the time preferences chapter reinforced previous findings that people value improvements in short-term QoL over long-term improvements. Given the emphasis on improvements in QoL (as demonstrated in Chapter 5), it is hardly surprising that so many weight-loss programs fail, when noticeable short-term improvements in QoL do not occur following weight loss (Chapter 3).

Much of the current literature on QoL and obesity has focused on cross-sectional studies or RCTs in specific populations. In view of the importance of QoL outcomes, it may be more beneficial to focus research on the implications on QoL of weight loss or weight gain. The results of such research will enhance our understanding of the relationship between obesity and QoL, as well as providing better estimates of changes in QoL for use in economic evaluations.

7.3 Policy implications

The overarching implication of the results of this research is that governments may be investing valuable resources in interventions that will not produce the intended results. This is partly due to exaggerated claims of cost-effectiveness and evidence based on short-term weight loss results. Further, the evidence from weight-loss trials may not reflect the preferences of overweight and obese individuals, which reduces the likelihood of uptake, long-term adherence and successful outcomes. The results from the DCE reported in Chapter 5 show that the failure of weight-loss interventions may in part be due to misalignment between individual preferences and the primary outcomes of clinical trials. A subset of overweight and obese individuals seems impervious to weight-loss interventions; one-quarter of respondents in the DCE reported that they would not enrol in the weight-loss program offered if it were available. While this estimate may not be accurate, it does indicate an overall reluctance to commit to a weight-loss program. From an economist's point of view, if these individuals are behaving rationally (maximising their utility from the consumption of unhealthy food), determining what, if any, incentives would influence their behaviour would be valuable. The economic notion of rationality assumes that individuals make unhealthy decisions as informed consumers (i.e., with full information). If individuals are making unhealthy decisions because they are poorly informed, intervention (government or otherwise) is warranted, as these individuals are failing to recognise the impact of their decisions on their current and future health and well-being. Moreover, overweight and obese individuals appear to have distinct preferences that need to be taken into account when designing interventions. This may aid in more successful long-term adherence and weight loss outcomes.

It has been suggested that one of the reasons for the rise in obesity levels is the increase in the availability of fast-food and ready-made meals. In other words, individuals are indicating their time preferences by choosing to consume high-calorie, inexpensive and unhealthy food rather than waiting longer for healthier home-cooked meals, as foods high in salt, fat or sugar generally taste better. It has also been theorised that obese individuals may be more impulsive (Hendrickson & Rasmussen, 2013). However, the research conducted for this thesis found no differences in time preferences between normal weight and obese respondents. If the hypothesis is that differences in time preferences are caused by differences in health and not the reverse, then incentives designed to change health behaviour may not be effective. Further research on incentives designed to change behaviour at the individual level would be beneficial, as well as determining whether people discount health and money differently.

An interesting result was the evidence for imperfect information demonstrated in the online survey. Comparing responses to the self-assessed weight questions with calculated BMI demonstrated that a substantial proportion of individuals did not realise that they were in a high-risk weight category. Only 48.2% of overweight respondents correctly perceived their weight, compared to 85.9% of normal weight individuals. The implications are that if they are under-estimating their weight, individuals may not fully understand how their diet and exercise choices affect their risk of comorbidities.

Furthermore, studying patterns of weight loss/gain is more important than a cross-sectional view. A cohort study in the Netherlands found that over a 15-year period, persistent obesity, or becoming overweight or obese, resulted in a lower QoL, compared with healthy weight (de Hollander et al., 2013). A limitation of this study is that it did not examine the pathway or direction of the association, as it was an observational study using only mean QoL at the end of the period as the outcome measure. Zheng et al. (2013) studied BMI trajectories over 16 years, with results suggesting that those individuals with BMI fluctuations had a higher mortality risk than static BMI status. A similar analysis could be conducted, using longitudinal data and QoL outcomes, to determine which pattern of weight gain/loss has the greatest impact on health-related QoL. In all the analyses throughout the thesis, the presence of long-term a health condition was significantly associated with poorer mental health and higher body weight. Disentangling the impact of long-term health conditions on mental health and obesity is an area that deserves more research.

Overall, the findings from this research has implications for current HTA of obesity interventions. If current evaluations of obesity interventions are overstating the gains in terms of cost-effectiveness and QoL. It is important to note that there are also many interventions aimed at the prevention of obesity (e.g. school-based interventions, food and nutrition policies, work-place interventions), however determining the cost-effectiveness of these intervention is fraught with difficulty given the difference in timing of costs and benefits, as well as determining the proper comparator. Moreover, there is ambiguity in the measurement of the benefits (in terms of QoL) of programs with outcomes aimed at avoiding a case of obesity in the future. This further poses problems for policy makers with limited budgets to prioritise funding between prevention interventions and treatments. Certainly, policies that encourage healthy eating and physical activity are beneficial, however, determining whether they are cost-effective remains an arduous task.

7.4 A final personal reflection

Within the context of obesity as a public health issue, finding the balance between freedom of choice and public policy is important in understanding the reasons for the success or failure of interventions. On one hand, there is an argument that people should be allowed to eat, drink and exercise in a manner that aligns with their personal desires and should be able to do so without government intervention. On the other hand, it is also argued that as society pays for (at least some of) the consequence of these negative behaviours, it therefore has the right to intervene, or to require individuals to be held responsible (Brown & Allison, 2013). In any discipline, finding a balance between these two ends of the ideological spectrum will always be a struggle. Economics provides a framework within which dietary and physical activity choices can be evaluated. From a policy perspective, the aim is to change 'unhealthy' behaviours and influence people to maintain and sustain healthy living. If there are market failures (such as negative externalities, imperfect information or irrational behaviour) due to individuals changing their responses to economic conditions, then government intervention is warranted. However, if individuals are behaving rationally, from an economic perspective, no intervention is required. Rational utility theory, which underpins economic theory, postulates that people's choices are considered optimal, as they are maximising their utility (making trade-offs in terms of health for the pleasure of eating unhealthy foods and not exercising), given their budgetary and time constraints. If this behaviour is considered rational, then understanding the choices individuals make with regards to unhealthy behaviours becomes essential. It is still unclear whether tackling obesity should be left to individuals making better choices about diet and physical activity, or whether public health interventions would be more efficient.

7.5 Concluding remarks

The research in this thesis focused on some on economic issues pertaining to obesity. Given the complex aetiology of obesity and the numerous simultaneous causes, it is difficult to disentangle the economic sources and consequences of obesity. However, the results from the thesis have demonstrated that there is an important association between obesity and QoL, and the failure to capture this properly is hindering the ability to accurately estimate the cost-effectiveness of obesity interventions. Overall, the social and economic burden of obesity is a major public health concern and the need to accurately develop interventions and assess their outcomes is pivotal in addressing the current epidemic. Economists may not have all the solutions but can play a part in tackling obesity.

In recent times we have seen life expectancy increase due to medical/scientific advances, improved sanitation and public health initiatives, among other general improvements, which has led to an overall increase in life expectancy (Haslam, 2007). If obesity rates continue to rise as predicted, there may be a devastating impact on overall morbidity and mortality, both here in Australia and globally. Indeed, if obesity levels continue to rise, it is plausible that the life expectancy of future generations will be lower than now. With the high cost of obesity – both the economic and health burden – an economic approach to the issue may provide additional insight. The burden of obesity is not only borne by individuals; governments, health care organisations and insurance companies likewise incur these societal costs. Understanding what drives individual behaviour choices around unhealthy behaviours that negatively affect body weight may be necessary to achieve economic efficiency.

8 APPENDICES

8.1 Appendix 1 - Proportion of overweight and obese in Australia

Proportion of overweight and obese persons aged 18 and over, by age group and sex, 2014–15												
	Men				Women				Persons			
	Overweight but not obese		Obese		Overweight but not obese		Obese		Overweight but not obese		Obese	
Age group	**%**	**95% CI**	**%**	**95% CI**	**%**	**95% CI**	**%**	**95% CI**	**%**	**95% CI**	**%**	**95% CI**
18–24	26.9	22.0–31.8	17.3	13.6–21.0	17.0	13.2–20.8	17.3	12.8–21.8	22.0	19.1–24.9	17.1	13.8–20.4
25–34	41.9	38.4–45.4	20.8	17.6–24.0	25.1	22.0–28.2	17.3	14.9–19.7	33.4	31.0–35.8	19.0	17.4–20.6
35–44	47.5	43.7–51.3	26.7	23.5–29.9	27.6	24.6–30.6	30.7	27.5–33.9	37.4	34.8–40.0	28.6	26.3–30.9
45–54	46.7	42.5–50.9	33.2	29.2–37.2	28.6	25.4–31.8	33.0	30.1–35.9	37.6	35.0–40.2	33.0	30.8–35.2
55–64	44.5	40.9–48.1	36.8	33.1–40.5	33.3	29.6–37.0	34.9	31.2–38.6	38.8	36.3–41.3	35.9	33.6–38.2
65–74	42.2	38.3–46.1	38.2	34.1–42.3	36.1	32.1–40.1	32.7	29.5–35.9	38.9	36.4–41.4	35.4	32.9–37.9
75–84	44.0	38.1–49.9	32.4	26.8–38.0	41.4	35.8–47.0	27.1	22.5–31.7	43.4	39.3–47.5	29.6	25.9–33.3
85 years and over	#47.3	36.0–58.6	11.2	3.4–19.0	35.0	25.1–44.9	21.5	14.2–28.8	38.8	30.2–47.4	17.8	13.4–22.2
Total 18 years and over	**42.4**	**41.0–43.8**	**28.4**	**26.9–29.9**	**28.8**	**27.6–30.0**	**27.4**	**26.1–28.7**	**35.5**	**34.6–36.4**	**27.9**	**26.9–28.9**

Proportion has a margin of error of >10 percentage points which should be considered when using this information.

Notes

1. Overweight and obesity classification is based on measured height and weight.
2. 95% CI = 95% confidence interval. We can be 95% confident that the true value is within this confidence interval.

Source: Australian Bureau of Statistics, 2015. National Health Survey: first results, 2014–15. ABS cat no. 4364.0.55.001. Canberra: ABS.

8.2 Appendix 2 - International Obesity Policies

Country	Policy	Description
USA	Co-payments	Expanded coverage of public Medicaid where co-payments can be waived when beneficiaries comply with specific wellness targets.
USA	Drink Up campaign	Promoted increasing the drinking of water promoted by the Partnership for a Healthier America
Japan	Health Examinations	Program to identify people at risk for metabolic syndrome and prevent its chronic disease consequences
United Kingdom	Public Health Responsibility Deal	Government sets targets and priorities and business partners make voluntary pledges contributing to the strategy.
Mexico	National Strategy for the Prevention and Control of Overweight, Obesity and Diabetes	Improved public health and surveillance, better medical care for people with chronic diseases, regulation and fiscal measures. Media campaign aimed at awareness of obesity and related chronic illnesses. Incentives for physicians to increase uptake and compliance of medication for those with chronic diseases.
Mexico	Regulatory framework	Food advertising to children labelling of processed foods and availability of food in schools and taxation of unhealthy food.
Mexico, Denmark, Finland, France, Hungary	Food taxes	Taxes and unhealthy foods.
UK	Food labelling	2013 – Voluntary consistent labelling scheme that combines traffic light colour coding – red, amber and green, with nutritional information showing the amount of fat, saturated fat, salt, sugar and calories in food products.
USA	Food Nutrition Labels (proposed)	Revise in serving sizes, display calories more prominently and include information on added sugars.
Chile	Law	Law on food labelling and advertising to incorporate easy-to-understand FOP labels with specific messages concerning critical nutrients, highlighting products high in sugar, salt and/or fat with a negative FOP tag.
Norway, Quebec	Ban on TV adverts	

Source: OECD obesity update, 2014.

8.3 Appendix 3 - Economic evaluation of obesity interventions literature search

Database: Embase <1974 to 2017 January 31>, Ovid MEDLINE(R) Epub Ahead of Print, In-Process & Other Non-Indexed Citations, Ovid MEDLINE(R) Daily and Ovid MEDLINE(R) <1946 to Present>
Search Strategy:

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1 *obesity/ (280667)
2 *overweight/ (94258)
3 (obesity or obese or overweight or body mass index or bmi).ab,ti. (897884)
4 1 or 2 or 3 (931728)
5 *cost effectiveness analysis/ (33745)
6 *cost utility analysis/ (8064)
7 qaly*.ab,ti. (21103)
8 cost effectiveness analysis.ab,ti. (18074)
9 cost utility analysis.ab,ti. (4437)
10 qaly.ab,ti. (17352)
11 *economic evaluation/ (11626)
12 economic evaluation.ab,ti. (16448)
13 5 or 6 or 8 or 9 or 11 or 12 (62198)
14 7 or 10 (21103)
15 13 and 14 (13148)
16 4 and 15 (281)
17 limit 16 to (adult <18 to 64 years> or aged <65+ years>) [Limit not valid in Ovid MEDLINE(R),Ovid MEDLINE(R) Daily Update,Ovid MEDLINE(R) In-Process,Ovid MEDLINE(R) Publisher; records were retained] (162)
18 limit 17 to yr="1995 -Current" (162)
19 limit 18 to ("adult (19 to 44 years)" or "middle age (45 to 64 years)" or "middle aged (45 plus years)" or "all aged (65 and over)" or "aged (80 and over)") [Limit not valid in Embase; records were retained] (134)
20 remove duplicates from 19 (101)
21 (editorial or erratum or letter or note or comment or commentary or conference abstract).pt. (6329869)
22 20 not 21 (84)
23 from 22 keep 2-3,9-10,12,15-16,19-20,23-26,29-32,35,37,43,45,51-52,56-57,59-62,64,67-68,71-73,76-79,82-84 (42)
24 "systematic review".ti. (141045)
25 (obesity or overweight).ti. (172695)
26 24 and 25 (1838)
27 limit 26 to yr="1995 -Current" (1836)
28 cost-effectiveness.ab,ti. (109726)
29 27 and 28 (38)
30 remove duplicates from 29 (24)
31 from 30 keep 1-24 (24)
32 23 or 31 (65)

8.4 Appendix 4 - Review of Cost-Effectiveness study characteristics of Obesity interventions

Source	Study design	Methodology	Results
Salkeld 1997	**Design** • *Model type:* Simulation model. Cohort starting with healthy individuals free from CVD. • *Intervention:* General practice-based lifestyle change program (follow-up 12-18 months): • Video group • Video + self help group • *Comparator:* Routine care. Authors justified selection. • *Time horizon:* Lifetime (stated in TUFTs database, however not explicitly stated in publication) **Population** Patients with risk factors for CVD, including BMI>25. **Locations, perspective** Australia, two perspectives presented: Health care payer Societal Primary care	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Changes in weight were not explicitly modelled.; ○ *Regain*: Changes in weight were not explicitly modelled.; ○ *Maintenance:* Changes in weight were not explicitly modelled. • *Comorbidities:* Framingham heart study was used as the basis of the logistic risk equations. Risk factors included age, sex, DBP, serum cholesterol, smoking, glucose intolerance and LVH. • *QoL/Utility:* Sourced from Australian study assessing quality of life after a CHD event.; ; Glasziou et al 1994 • *Attrition:* Data were based on patients that remained in the trial that had complete data. Drop out ranged frm 26% to 49% across study arms. **Outcomes** • $/QALY • Life year saved • Changes in life expectancy, CHD events, and related costs. *CE threshold:* • *None stated* • *Discounting:* 5% • *Currency, year:* AUD ($), 1994 **Quality rating (TUFTS):** 5.5	**Key findings** *Base case* *TUFTS:* • Video+self help vs routine care: • Females: 1.3e+0.007/QALY • Male: $180k/QALY • Video vs routine care: • High risk males: $35k/QALY.; *Publication:* • Males: $152,128 / QALY • High risk males: $29,574 / QALY • *Sensitivity analyses* Scenario analysis presented. Societal perspective including productivity gains presented as sensitivity analysis, which did not have a significant effect on the overall results. Maintenance of behavioural risk factors from one to two years reduced ICER. **Authors conclusions** ICERs were high for makes ($152k/QALY) and extreme for females (exceeded $11M/QALY) **Additional notes** *Funding/conflict of interest:* Funded by Government The model was sensitive to key assumptions of effectiveness of intervention over time and drop out.

			Authors concluded that CE of the gneral practice-based lifestyle interventions were yet to be demonstrated.
Avenell 2004	**Design** • *Model type:* Markov model • *Intervention:* Low fat diet and exercise, including dietician and supervised exercise sessions. • *Comparator:* Oral and written information about diet and exercise at baseline visit. • *Time horizon:* 6 years (sensitivity done for 15 years) **Population** People with impaired glucose tolerance aged 55+ **Locations, perspective** UK, health care payer Primary care	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Changes in weight were not explicitly modelled. Authors rationalised that weight losshas the potential benefit of reducing risk of comorbidiites.; ○ *Regain*: Changes in weight were not explicitly modelled.; ○ *Maintenance:* Changes in weight were not explicitly modelled. • *Comorbidities:* Used in sensitivity analyses and not included in base case. • *QoL/Utility:* ; Differences in quality of life based on diabetes.; Harvard University datsbase (diabetics, CHF, IDDM), Hakim 2002, Clegg 2003. • *Attrition:* Participation was discussed as the rate varied from 50% to 85% at various centres, however it is unclear how this was applied in the model. **Outcomes** • $/QALY gained *CE threshold:* • *None stated* • *Discounting:* QALYs 1.5% /Costs 6% • *Currency, year:* GBP (£), 2001 **Quality rating (TUFTS):** [not in TUFTs]	**Key findings** *Base case* *TUFTS:* • Not in TUFTs; *Publication:* • £113,905 per QALY in Year 1, reducing to £13,389 per QALY in Year 6. • *Sensitivity analyses* Univariate and scenario analyses. Other disease impacts are considered in the sensitivity analyses (?results of sensivity). Model was sensivite to QoL applied. Increasing cost of intervention reduced ICER. Increasing time horizon reduced ICER substantially. **Authors conclusions** Intevention was deemed cost-effective (dominant) **Additional notes** *Funding/conflict of interest:* None declared. Research funding from Pharmaceutical Company, Roche. Weight is often regained within 5 years following many of the lifestyle (as well as drug) trials reviewed earlier means that a high degree of caution should be applied in extending the results
Tsai 2005	**Design** • *Model type:* Trial based model • *Intervention:* Low carbohydrate diet	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Trial based results applied with numerical differences at 6 months and one year (although difference	**Key findings** *Base case* *TUFTS:* • Cost-saving;

	• *Comparator:* Standard diet • *Time horizon:* One year **Population** Severely obese people **Locations, perspective** USA, societal Primary care	in weight loss between diet groups was not signficant after 1 year); ○ *Regain*: `-; ○ *Maintenance:* `- • *Comorbidities:* Not included. • *QoL/Utility:* SF-36; Trial based SF-36 scores were used to derive SF-6D scores. However trial results showed there was no difference at 6 or 12 months observed in the trial.; Trial based SF-36 (Stern et al 2003, 2004) • *Attrition:* Attrition was 37% in intervention group and 31% in comparator at 1 year. Authors commented that evaluation of QALYs was complicated by attrition at 6 and 12 months. **Outcomes** • $/QALY *CE threshold:* • *US$ 50K* • *US$ 100K* • *US$ 150,000* • *Discounting:* NA - time horizon was one year. • *Currency, year:* USD ($), 2001 **Quality rating (TUFTS):** 5	*Publication:* • -$1225/QALY i.e. intervention (low carb diet) dominated the standard diet, however range of CERs wide with an undefined 95% CI (bootstrap analysis). • *Sensitivity analyses* Univariate, multivariate and probalistic analyses. CEAC presented. Results were not sensitive to analyses conducted **Authors conclusions** Low carbohydrate diets were not more cost effective than a standard diet for weight loss. **Additional notes** *Funding/conflict of interest:* Funded by Government
Roux 2006	**Design** • *Model type:* First order monte carlo micro-simulation model • *Intervention:* 6 month intervention and 6 months maintenance: • Diet only • Diet and pharmacotherapy • Diet and exercise	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* BMI distribution based on data from the third National Health and Nutrition Examination Survey (NHANES III). ○ Probablility of weight loss at 6 months: ranged from 0.05 (routine care) to 0.95 (diet, exercise and behaviour modification).; ○ *Regain*: BMI is annually adjusted for aged related increases in the absence of intevention.;	**Key findings** *Base case* *TUFTS:* • $17,000/QALY; *Publication:* • Dominated to $12,640/QALY • *Sensitivity analyses* Bounded sensitivity analyses.

	• Diet, exercise and behaviour modification • *Comparator:* Routine care • *Time horizon:* Lifetime **Population** Healthy, overweight (BMI ≥ 25 kg/m2) 35 year old women. **Locations, perspective** USA, societal Urban	○ *Maintenance:* Probability of weight loss maintenance at 1 year: ranged from 0.5 (routine care) to 0.67 (diet, exercise and behaviour modification). ○ Probability of lon-term weight loss maintenance (5 years) programs with lifestyle modification: 0.2 • *Comorbidities:* Age and BMI-specific obesity disease complications, that are assumed to be lifelong, and predispose affected women to a greater risk of CHD. • *QoL/Utility:* ; Temporary QoL decrements assumed to be related to the intensity of effort required to participate in a particular weight loss programme (inconvenience); Disease specific quality weights: obesity, 10% weight loss, CHD, T2DM (Fryback 1993). • No source given for obesity and weight loss quality weights. • *Attrition:* Probability of program compliance: routine care (1.0); diet, exercise and behaviour modification (0.9) **Outcomes** • $/QALY gained • $/year of life saved *CE threshold:* • *US $50K* • *Discounting:* 3% • *Currency, year:* USD ($), 2001 **Quality rating (TUFTS):** 5	Results were most sensitive to assumption of obesity related QoL and the likelihood of long term weight loss maintenance. **Authors conclusions** Multidisciplinary weight loss program incuding diet, exercise and behaviour modification provides good value for money, but more research is required to confirm the impacts on QoL **Additional notes** *Funding/conflict of interest:* Funded by Foundation
Annemans 2007	**Design** • *Model type:* Markov model • *Intervention:* Physical exercise • *Comparator:* No intervention • *Time horizon:* 25 years	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Incidence of diabetes related to body weight were modelled (Warren et al 2004: CEA of sibutramine); ○ *Regain*: -; ○ *Maintenance:* -	**Key findings** *Base case* *TUFTS:* • Aged 50 years: $3,700/QALY • Aged 40 years: $15,000/QALY • Aged 30 years: $22,000/QALY;

	Population Persons at risk: with hypertension and/or hypercholesterolaemia and/or obesity. Initial state is without complications. **Locations, perspective** Belgium, societal (includes health care payer subsidising intervention) fitness setting	• *Comorbidities:* Included - modelled as different states (CVD CHD, diabetes, colon cancer, breast cancer) • *QoL/Utility:* Per unit increase in BMI, 0.021 utility is lost. • Decrements applied for events TIA (0.044), stroke (0.072), CVD (0.052), breast cancer (0.19), and colon cancer (0.27), and for female sex (0.038).; ; HRQoL study estimating independent effect of BMI and complications in diabetic patients (Coffey et al. 2002). Utility of diabetic patients is 95% of non-diabetic patients (Warren et al 2004); • *Attrition:* Model assumed 100% compliance with physical exercise. **Outcomes** • $/QALY gained. *CE threshold:* • • *€20K/QALY* • *Discounting:* 3% • *Currency, year:* EUR (€), 2004 **Quality rating (TUFTS):** 4.5	*Publication:* • €2000 to €15000 per QALY • *Sensitivity analyses* Univariate and multivariate analyses. Variation in time horizon did not influence cost-effectiveness. Observations with a longer time horizon require a larger investment that is proportional to the savings and health benefits obtained. Model was sensitive to assumptions of reduced adherence to exercise. **Authors conclusions** Intevention was deemed cost-effective **Additional notes** *Funding/conflict of interest:* Study was sponsored by an unrestricted grant from the Fitness Organisation.
Dalziel 2007	**Design** • *Model type:* Markov model (Four models built - two disease models and two behavioural models). • *Intervention:* 8 Different interventions described • *Comparator:* Controls varied • *Time horizon:* 20 years (except for the reduced fata diet for IGT intervention, which was restricted to 5 years, behavioural model)	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Weight was only included as an explicit variable in one of the four models (FFFF).; ○ *Regain*: States: Normal, overweight and obese. Transitions applied in year 1, with a 50% relapse rate applied in year 2.; ○ *Maintenance:* • *Comorbidities:* • *QoL/Utility:* ; relationship between: mortality and QoL were modelled.; BMI model - AqoL: McNeil and Segal 1999	**Key findings** *Base case* *TUFTS:* • Not in TUFTs; *Publication:* • Range for programs:intervention dominates to $19800/QALY • *Sensitivity analyses* Univariate sensitivity analyses.

	Population General population **Locations, perspective** Australia, societal Community	• Fruit and vegetable model - SF-36: Brazier 2002 and National Nutrition survey (ABS 2001. • Cardiac model - TTO: • Derdeyn and Powers 1996; Kuntz et al., 1996; Lee et al., 1997. • diabetes model - EQ-5D: Colagiuri et al., 2003) • *Attrition:* Relationship between behaviour and/or clinical parameters modelled. Behavioural outcome data for both media campaigns were highly uncertain. **Outcomes** *CE threshold:* • *(WHO 2006) 'cost effective defined as 1-3 times GDP/head equal to AUD$ 11,427 to AUD$ 33,786 in June 2005.* • *'very cost-effective' less than GDP/head* • *Discounting:* • *Currency, year:* AUD ($) 2003 were converted to USD ($) and EUR (€) using exchange rates in June 2006. **Quality rating (TUFTS):** Not in TUFTs	Varying estimates of effect size, cost, utility, time horizon and discount rate. Behavioural outcome data for both media campaigns were highly uncertain (poorer quality trial results). **Authors conclusions** All interventions subject to economic evaluation appeared cost-effective relative to societal norms. **Additional notes** *Funding/conflict of interest:* Work was funded by Monary University and the Australian DoHA.
Galani 2007	**Design** • *Model type:* Markov model • *Intervention:* Three year lifestyle intervention with advice, counselling, consultations with dietician and regular group based exercise • *Comparator:* No intervention for overweight. Obese participants received basic dietary counselling • *Time horizon:* 60 years (mininum starting age 25 years, max. age of 85 years) (lifetime)	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Treatment effect is modelled as reduction in BMI [change in overweight: -1.11kg/m2; obese -1.33kg/m2]; ○ *Regain*: After the first 6 years, subjects linearly gain weight for 4 years returning to baseline i.e. after 10 years weight returns to the initial weight (Lindstrom 2006).; ○ *Maintenance:* Effects of lifestyle intervention on CV risk factors and weight loss is maintained for 6 years. • *Comorbidities:* Treatment effect modelled as eduction in other risk factors SBP, TC, HDLC (Lindstrom 2005). Effect is not additive or multiplicative (hypertension, diabetes, hypercholesterolaemia, stroke, CHD). Health states are	**Key findings** *Base case* *TUFTS:* • Not reported in TUFTs.; *Publication:* • Males, CHF/QALY ranges from -2560 to 395 • Females, CHF/QALY ranges from -2000 to 4515 • [See Table 4 in full text of publication, CHF/QALY by age group, discounted by 3% and undiscounted] • *Sensitivity analyses* Probablistic sensitivity analysis conducted.

	Population Individuals aged 25+ with BMI ≥ 27 kg/m2 overweight or BMI ≥ 33 kg/m2 (obese) **Locations, perspective** Switzerland, societal Primary care	separate and are not mutually exclusive for each comorbidity. • *QoL/Utility:* ; Study (Macran 2004) assessed the relationship between BMI and utility scores.; Utilities for overweight and obese people (Macran 2004), utilities changes due to decreases in BMI (Hakim 2002) and utilities associated with the complications of obesity (Jia 2005). • *Attrition:* Not explicitly modelled. Authors did not include compliance to lifestyle programme in their model. **Outcomes** • CHF/QALY gained *CE threshold:* • *None.* • *Discounting:* 3% • *Currency, year:* CHF, 2006 **Quality rating (TUFTS):** Not reported in TUFTs.	(variation weight maintenance/regain is not tested in sensitvity) **Authors conclusions** Lifestyle intervention is cost-effective in the long-term prevention and treatment of obesity. **Additional notes** *Funding/conflict of interest:* Work was funded by the Swiss Federal Office of Health.
McConnon 2007	**Design** • *Model type:* Trial based model • *Intervention:* Internet-based programme: advice, tools and information to support behavioural change, and enable participants to manage their own care (12 months) • *Comparator:* Usual care: continue with usual approach to weight loss. • *Time horizon:* One year **Population** Individuals aged from 18-65 years with BMI ≥ 30 kg/m2	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Trial based at 12 months - mean difference in BMI 0.3 (95% CI -0.4, 1); ○ *Regain*: `-;   ○ *Maintenance:* `- • *Comorbidities:* Not included • *QoL/Utility:* ; Quality of life increased for both groups over the trial, however no significant difference between groups.; Trial based at 12 months, EQ-5D. • *Attrition:* Just over half the participants used the website after 6 months, decreasing to one third at 12 months. • No signficant differences in dietary habits or confidence scores over 12 months.	**Key findings** *Base case* *TUFTS:* • $87,000/QALY; *Publication:* • £39,248/QALY • *Sensitivity analyses* Univariate, multivariate and probalistic analyses. Results were sensitive to assumptions pertaining to study attrition, utilitsation of the intervention. **Authors conclusions**

	Locations, perspective UK, societal perspective Primary care	**Outcomes** • £/QALY *CE threshold:* • *CEAC presented.* • *£20K-£30K/QALY* • *Discounting:* NA - time horizon was one year. • *Currency, year:* GBP (£), 2005 (not explicitly stated) **Quality rating (TUFTS):** 5	Intervention (internet based tool) did not provide additional benefits. Authors reason that the result of no difference is likely due to the population having reduced attrition for intervention. **Additional notes** *Funding/conflict of interest:*

Bemelmans 2008	**Design**
	• *Model type:* dynamic Markov-type multi state transition model
	• *Intervention:* Lifestyle programme: community based approach (90% of population) and intensive approach (10% of population).
	• *Comparator:* No intervention
	• *Time horizon:* 20-80 years
	
	Population
	BMI ≥ 25 kg/m2
	
	Locations, perspective
	Netherlands, Health care payer
	Primary care
		Assumptions and variables
		• *Weight assumptions:*
		  ○ *Loss:* Reduction of BMI during 5 year period:
		  ○ community based approach 0.2 kg/m2
		  ○ Intensive lifestyle program 0.8 kg/m2.;
		  ○ *Regain*: No assumptions modelled. Upward trend in prevalence was only discussed and not included in the model;
		  ○ *Maintenance:* Not explicitly included in the model.
		• *Comorbidities:* Absolute number of diseases prevented: CVD, T2DM, cancers, musculoskeletal conditions.
		• *QoL/Utility:* ; QALYs were calculated by coupling disease prevalence rates to disability weights (DALYs).; Global Burden of Disease, DALYs (Murray 1994, Stouthard 1997, Mathers 2001)
		• *Attrition:* Prevalence of inactivity will reduce up to 2%.
		
		Outcomes
		• €/QALY gained
		• €/LY gained
		• QALYs saved
		• LY saved
			Key findings
			Base case
			TUFTS:
			• $8900/QALY (combined);
			Publication:
			• Combined implementation €5700/QALYG
			• Community based approach: €5100/QALYG
			• Intensive lifestyle program: €8400/QALYG
			
			• *Sensitivity analyses*
			Univariate analyses.
			Authors concluded that the model was not sensitive to variations in costs, effects, time horizon and discount rates.
			
			Authors conclusions
			Inteventions were deemed cost-effective
			
			Additional notes
			Funding/conflict of interest: Funded by Government

		• Cumulative number of diseases prevented (CVD, T2DM, cacner, musculoskeletal conditions). *CE threshold:* • *No* • *Discounting:* 4% • *Currency, year:* EUR (€), 2004 **Quality rating (TUFTS):** 3	

Roux 2008	**Design**
	• *Model type:* Flexible state-transition Markov model
	• *Intervention:* Four strategies:
	• Community wide campaign
	• Individually adapted health behaviour change
	• Community social support interventions
	• Creation/enhanced access to physical activity information and opportunities.
	• *Comparator:* No intervention
	• *Time horizon:* Lifetime (40 years)
	
	Population
	Adult population (25-64 years) with no diseases (CHD, ischaemic stroke, T2DM, breast cancer, colorectal cancer).
	
	Locations, perspective
	USA, societal
	Community
		Assumptions and variables
		• *Weight assumptions:*
		  ○ *Loss:* Four physical activity levels modelled based on MET-minutes per week, which captures duration, intensity and frequency of physical activity. (add footnote- One unit of MET represents the metabolic rate equivalent of consuming 3.5mL of oxygen per kg of bod;
		  ○ *Regain*: Decline in effectiveness after intervention ended (ranging from 33-50% decline).;
		  ○ *Maintenance:* -
		• *Comorbidities:* CHD, ischaemic stroke, T2DM, breast cancer, colorectal cancer were modelled. All interventions reduced disease incidence.
		• *QoL/Utility:* ; Multiple regressions of QoL as a function of age, gender, disease, and physical activity.; Quality of Life Wellbeing derived from the National Health Interview Survey 2001.
		• *Attrition:* Not included in model.
		
		Outcomes
		• $/QALY gained
		• $/LY gained
		CE threshold:
		• *CEAC presented.*
		• *Discounting:* Costs: 3%
			Key findings
			Base case
			TUFTS:
			• $18K to $88K/QALY;
			Publication:
			• $14K to $69K/QALYG
			
			• *Sensitivity analyses*
			Univariate, multivariate, and probabilistic
			Reducing time horizon influenced CE substantially.
			Results were sensitive to intervention-related costs and effect size.
			
			Authors conclusions
			All the physical activity interventions were cost effective compared well to other well accepted preventative measures. Results supported using the interventions.
			
			Additional notes
			Funding/conflict of interest: Funded by Foundation

		• Annual medical inflation facto rapplied: 8% • *Currency, year:* USD ($), 2003 **Quality rating (TUFTS):** 5.5	
Eriksson 2010	**Design** • *Model type:* Trial based general linear model. • *Intervention:* Supervised exercise sessions, diet counciling and regular group meetings. • *Comparator:* Standard care • *Time horizon:* 3 years **Population** Adults at moderate to high risk CVD. **Locations, perspective** Sweden, societal Primary care	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Study did not use weight as a model input or outcome. However, the authors assumed that an increase of physcial activity affects overweight individuals by delaying onset of chronic conditions, such as T2DM and reducing CV risk.; ○ *Regain*: Not applicable; ○ *Maintenance:* Not applicable. • *Comorbidities:* Not modelled explicitly. However, the authors assumed that an increase of physcial activity affects overweight individuals by delaying onset of chronic conditions, such as T2DM and reducing CV risk. • *QoL/Utility:* ; Assumed causality between higher level of physical activity and quality of life.; Trial based - EQ-5D-5L and EQ-VAS, SF-36, SF-6D • *Attrition:* Attrition was low and data were analysed on an ITT basis. **Outcomes** • $/QALY gained • NMB (95% CI) *CE threshold:* • *CEAC presented.* • *$50k/QALYG* • *Discounting:* 3% • *Currency, year:* USD ($), 2009 [costs transformed from Swedish Krona to USD using exhange rate 1USD=7.5 Swedish Krona]	**Key findings** *Base case* *TUFTS:* • Cost saving; *Publication:* • $1668 to $4813/QALY gained. • *Sensitivity analyses* Probabilistic, univariate and multivariate analyses. QALYS gained using different QoL instruments presented: (intervention vs control, discounted) EQ-5D: 0.08 (p=0.24) EQ-VAS: 0.20 (p<.01) SF-6D: 0.07 (p= 0.03) Results are not sensitive to doubled costs of intervention, **Authors conclusions** Authors claimed intervention is cost-saving. **Additional notes** *Funding/conflict of interest:* Funded by the Norrbotten Local County Council, Division of Primary Health Care, Lulea° , Sweden; Visare Norr, Northern County Councils, Sweden; and the Heart Foundation of Northern Sweden.

		Quality rating (TUFTS): 5.5	Participant exercise time was not considered in the analysis, for some individuals, this time may represent a loss of enjoyment when spending time on exercise.

HTA 2010	**Design**
	• *Model type:* Micro-simulation model
	• *Intervention:* Various public health programmes [decribed in other publications].
	• *Comparator:* No intervention.
	• *Time horizon:* Lifetime (ending at age 60)
	
	Population
	General population (aged between 2 and 75 years)
	
	Locations, perspective
	New Zealand, Health care payer
	Community
		Assumptions and variables
		• *Weight assumptions:*
		  ○ *Loss:*
		  ○ The reduction in BMI first observed would apply in Year 1 and applied each year up until Year 5 (even if decrease was observed in the trials later than Year 1 amd not observed in subsequent years).;
		  ○ *Regain*: The reduction in BMI of the intervention relative to the control would decay by 1% per annum after the 5th year.;
		  ○ *Maintenance:* Not modelled.
		• *Comorbidities:* Intervention has impact on BMI
		• Overweight or obese individuals have increased likelihood of contracting one of 14 (mutally exclusive) chronic illnesses.
		• Obesity related illness, modelled as separate states: MI, CHD, CHF, CVA, diabetes, arthrosclerosis (hip), arthrosclerosis (knee), dorsopathies, Rectal cancer, colon cancer, breast cancer, prostate cancer, kidney cancer, endometrium cancer.
		• *QoL/Utility:* Utility weights applied represent the average quality of life over the duration of the illness.; Good health - perfect health (?overestimation); Utility weights for chronic condition states: Mittman et al (1999) [except osteoarthritis: Marshall et al (2008); Grinrod et al (2010)]; assumed utility of 1 applied to good health state.
		• *Attrition:* Not stated, but modellers assume that there is 100% compliance in the intervention arm.
		
		Outcomes
		• $/QALY gained
			Key findings
			Base case
			TUFTS:
			• Not in TUFTs;
			Publication:
			• $QALY gained for each programme ranges from $4824 to $205,101
			
			• *Sensitivity analyses*
			Univariate and scenario analyses.
			Results were sensitive to: age interventions were initiated. The age between childhood and middle-age adult are where interventions were most cost-effective; decay of intervention effect, increasing the rate of decay above 1% increased the ICER; reducing time horizon increased ICER.
			
			Authors conclusions
			Authors caution reader that analyses are exploratory and should not draw conclusions of CE based on the analyses.
			
			Additional notes
			Funding/conflict of interest: Funded by the Health Research Council of New Zealand.
			The authors did not consider assumptions of compliance to programes or weight gain.

		CE threshold: • *$15,000 and $50,000 per QALY* • *Discounting:* 3.5% • *Currency, year:* NZD ($), 2006 **Quality rating (TUFTS):** Not in TUFTs	
Trueman 2010	**Design** • *Model type:* Trial based + micro-simulation model • *Intervention:* Counterweight, GP weight management advisors (one year) • *Comparator:* No intervention • *Time horizon:* Lifetime **Population** General population **Locations, perspective** UK, Health care payer Primary care	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* The model intended to mirror underlying population trends in body weight. Every 6 months, individuals either loses, gains or has stable weight. ○ One fifth of the population lose weight. ○ Intervention effectiveness was assumed a mean 3 kg weight loss at 12; ○ *Regain*: Two fifths of the population gain weight. ○ Background weight gain: average 1 kg/year weight gain. ○ Base case (intervention): weight was regained after 2 years i.e. at year 3.; ○ *Maintenance:* Two fifths of the population maintain weight. • *Comorbidities:* Multiple morbidities were assumed to have a multiplicative effect. • Diabetes was considered a chronic condition impacting only on quality of life and assumed not to impact mortality. • *QoL/Utility:* • Utilities were associated each health states, and by age and gender applied based on published sources. Multipliers (diabetes 0.8661, CHD 0.8670, colon cancer 0.95) were applied to the utility score to obtain the utility for individuals who developed any; ; By BMI and age (Macran 2004); diabetes and CHD (Ara 2005); colon cancer (Lewis 2002);	**Key findings** *Base case* *TUFTS:* • Cost-saving; *Publication:* • Intervention dominant (range: dominant to £2651/ QALY) • *Sensitivity analyses* Univariate sensitivity analyses. Different scenarios of weight loss, background weight gain and drop out. Reducing background weight gain increased ICER, however intervention was still considered cost-effective. Even assuming dropouts/non-attenders at 12 months (55%) lost no weight and gained at the background rate, intervention was dominant. **Authors conclusions** Intervention was cost-saving and highly cost-effective. **Additional notes** *Funding/conflict of interest:* Funding over time received from various parties: Roche Products Ltd, Scottish Government, sanofi-aventis.

		• *Attrition:* Effectivness was modelled using a mean -3 kg weight loss at 12-months was assumed based response rate at 12 months of completers (45%). **Outcomes** • $/QALY *CE threshold:* • *£20K-30K/QALY* • *Discounting:* 3.5% • *Currency, year:* GBP (£), 2005 **Quality rating (TUFTS):** 4.5	

Ginsberg 2012	**Design**
	• *Model type:* [not stated - appears that authors used an a budget impact analysis approach that incorporating utility]
	• *Intervention:* Adoption of eight interventions: the National Prevention and Health Promotion Program
	• *Comparator:* The comparator is unclear.
	• *Time horizon:* Range: one year to lifetime.
	
	Population
	General population
	
	Locations, perspective
	Israel, societal
	Primary care and community
		Assumptions and variables
		• *Weight assumptions:*
		  ○ *Loss:* Expected average decreases in BMI ranged from 0.05 to 0.90.
		  ○ The mean weight lost was reduced over time to recidivism.;
		  ○ *Regain*:
		  ○ Regaining weight either back to their initial weight or beyond initial weight were not modelled.;
		  ○ *Maintenance:* No explicitly modelled.
		• *Comorbidities:* Not included in model.
		• *QoL/Utility:* BMI changes were converted to QALY gains based on Tsai 2005.; ; Tsai 2005
		• *Attrition:* Not clear.
		
		Outcomes
		• NIS/QALY
		• Cost savings by BMI level
		CE threshold:
		• *NIS 312,483 (3x GNP per capita)*
			Key findings
			Base case
			TUFTS:
			• $14K/QALY;
			Publication:
			• NIS 47,559/QALY (US$14,000/QALY)
			• NIS 11,812 – NIS 83,355 (sensitivity analysis change in recidivism rat from 20%-80%)
			
			• *Sensitivity analyses*
			Univariate analyses.
			Model was highly sensitive to recindivism rates.
			
			Authors conclusions
			CUA supports intervention.
			
			Additional notes
			Funding/conflict of interest: Funded by Government

		• *Discounting:* 3% • *Currency, year:* New Israeli Shekels (NIS), 2010 **Quality rating (TUFTS):** 3.5	It appears that authors used an a budget impact analysis approach that incorporating utility, which is different to all other models types identifed in the literature search. A market share approach where the number of people in the market were allocate
Miners 2012	**Design** • *Model type:* Discrete event similation model. • *Intervention:* E-learning device to support behavioural changes in dietrary and exercise patterns • *Comparator:* Standard care • *Time horizon:* Lifetime **Population** Obese adults (50 years old) with BMI ≥ 30 kg/m2 **Locations, perspective** UK, health care payer [Setting not specified, applicability not addressed.]	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* BMI was selected as the main model driver. ○ Natural history of BMI modelled; BMI increased with age, the mean BMI, the likelihood of disease and death due to obesity increased. ○ Non-statistically weighted mean difference in favoured of interventon.; ○ *Regain*: Time to developing a disease was shorter for individuals with high BMI than lower BMIs. Mean increase in weight over 4 years is 1 kg/year -applied to all patients.; ○ *Maintenance:* `- • *Comorbidities:* Time to develop CVD and T2DM were shorted in individuals with high BMI. • Risk of CVD (QRISK2), T2DM (Stern 2002; Lindstom 2003) • *QoL/Utility:* ; Study (Macran 2004) assessed the relationship between BMI and utility scores.; EQ-5D sourced from literature (Macran 2004) • *Attrition:* High attrition rates are a defining feature of weight loss/preventing weight gain interventions. The probability that individuals stopped treatment before 12 months, for reasons other than developing disease or death was included. No differences between t **Outcomes** • £/QALY gained. *CE threshold:*	**Key findings** *Base case* *TUFTS:* • $160k to $300k; *Publication:* • £102,000 - £232,000/QALY • *Sensitivity analyses* Univariate analyses. Model was sensitive to assumed fixed costs associated withthe e-learning devices, the relative treatment effect, the rate at which health outcomes were discounted and the duration of treatment effect. **Authors conclusions** Unlikely to be cost-effective unless their fixed costs are much lower than estimated or future devices prove to be much more effective. **Additional notes** *Funding/conflict of interest:* Funded by Government Authors stated the model results suggest that under most circumstances, e-LDs are unlikely to be cost-effective at any reasonable WTP threshold.

		• *CEAC presented.* • *£20K to £30K per QALY gained.* • *Discounting:* 3.5% • *Currency, year:* GBP (£) 2009 **Quality rating (TUFTS):** 5.5	
van Weir 2012	**Design** • *Model type:* Trial based model • *Intervention:* Distance lifestyle councilling (telephone and internet) • *Comparator:* Self-help • *Time horizon:* Two years **Population** Employed persons with BMI ≥ 25kg/m2 **Locations, perspective** The Netherlands, societal and business Business setting - employed persons	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* In trial weight loss difference (vs control): ○ Phone 0.3 kg (95% CI -0.6, 1.3) ○ Internet 0.9 kg (95% CI -0.1, 1.96); ○ *Regain*: `-; ○ *Maintenance:* `- • *Comorbidities:* None included. • *QoL/Utility:* In trial weight loss difference (vs control): • Phone 0.001 (95% CI -0.03, 0.03) • Internet 0.01 (95% CI -0..1, 0.04); No significant difference between the groups.; Trial based EQ-5D. • *Attrition:* High attrition in the study (45%). Body weight and cost variables were complete for 30% of the participants; Utilities and costs were complete for 28% participants. Missing data were imputed: body weight 43%, health utilities 41%, and cost 57%. **Outcomes** • €/QALY *CE threshold:* • *CEAC presented.* • *€20K/QALY* • *Discounting:* Costs: 4% • Outcomes: 1.5%	**Key findings** *Base case* *TUFTS:* • Phone: $550K/QALY • Internet: $2100/QALY; *Publication:* • Phone: €245,243/QALY • Internet: €1337/QALY • *Sensitivity analyses* Probabilistic, univariate and multivariate analyses. Sensitivity analyses generally confirmed the results from the main analyses. **Authors conclusions** Alhtough, the internet based program appears to be the preferred intervention, neither intervention mode was proven to be cost-effective compared to self-help. **Additional notes** *Funding/conflict of interest:* Funded by the Netherlands Organization for Health Research and Development

		• *Currency, year:* EUR (€), 2004 **Quality rating (TUFTS):** 6	
Au 2013	**Design** • *Model type:* Markov model (based on model from Galani 2007) • *Intervention:* Standard behavioural therapy (6 months) combined with provision of meal plans and shopping lists. • *Comparator:* 1) Standard behavioural therapy (6 months) only; 2) do nothing. • *Time horizon:* Lifetime (40 years) **Population** Overweight or obese adult women (BMI of 33 kg/m2) **Locations, perspective** UK, health system	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Weight loss up to week 26 (-1.5kg/m2).; ○ *Regain*: ○ Weight regain per month from week 26 to week 78 was linear (SBT 0.39 kg and SBT+list 0.43 kg) and continued until participants returned to the baseline BMI of 33 kg/m2.; ○ *Maintenance:* `- • *Comorbidities:* Included as health states: hypertension, diabetes, hypercholesterolaemia, stroke, CHD, colorectal cancer, osteoarthritis (not additive or multiplicative) • *QoL/Utility:* Utility decrements associated with each health condition were subtracted from the utility estimate of normal weight individuals from the UK population. • Normal weight people do not suffer from comorbidities associated with being overweight or obesity. • Lar; ; Literature based values (Kinge 2010; Jia 2005; Sach 2007; Ara 2008; Ara 2011) • *Attrition:* Adherence to the programme was not included (assumed 100% compliance). Adherence was not tested in a sensitivity analysis. **Outcomes** • £/QALY *CE threshold:* • *£20K/QALY* • *Discounting:* 3.5% • *Currency, year:* GBP (£), 2010	**Key findings** *Base case* *TUFTS:* • $280/QALY (Cost-saving); *Publication:* • SBT+list vs do nothing: base case, £166/QALY (best case, dominates to worst case, £2455/QALY) • SBT+list vs SBT: base case, SBT+list dominates (best case dominates to worst case £1720/QALY) • *Sensitivity analyses* Univariate and multivariate analyses. The intervention strategy remained dominant or cost-effective under various scenarios. Results were sensitive to treatment effect, intervention costs, and disease state costs. **Authors conclusions** Intevention was deemed cost-effective (dominant) **Additional notes** *Funding/conflict of interest:* None declared.

		Quality rating (TUFTS): 5	
Fuller 2013	**Design** • *Model type:* Trial based model • *Intervention:* Weight loss program by commerical provider (12 months) • *Comparator:* Weight loss program based on standard care (12 months) • *Time horizon:* One year **Population** Adults (≥18 years) with BMI 27-35kg/m2. **Locations, perspective** Australia, UK and Germany Perspective: health care funder and societal. Primary care	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Trial based results: different in weight loss at 12 months between groups was statistically significant in all countries.; ○ *Regain*: `-; ○ *Maintenance:* `- • *Comorbidities:* Not included. • *QoL/Utility:* ; ; Trial based: Impact of Weight on Quality of Life Questionnaire-Lite (IWQOL-Lite) (Kolotkin 2001; Mueller 2011). Utility was derived using algorithm to SF-6D (Brazier 2004) • *Attrition:* Trial based results of ITT and completers were compared. **Outcomes** • $/kg weight loss • $/QALY gained *CE threshold:* • *AUS: $50k/QALYG* • *UK: £20-30K/QALYG* • *GER: €50K/QALYG* • *Discounting:* NA - time horizon was one year. • *Currency, year:* AUD ($), EUR (€), GBP (£), 2011. • Fx rate: 1 AUD = 1.01 USD; 1 GBP = 1.64 USD; 1 EUR = 1.42 USD **Quality rating (TUFTS):** Not in TUFTs	**Key findings** *Base case* *TUFTS:* • Not in TUFTs; *Publication:* • ICER, intervention vs standard care: • health-sector perspective ($USD/QALY): Australia $18266, UK $12100 and Germany $40933. • Societal ($USD/QALY): Australia $31663, UK $24996, Germany $51571. • *Sensitivity analyses* Univariate anlayses. Additional medication costs, and costs of referring to alied health professional in the standard care group. Sensitivity analyses conducted did not test uncertainty of uptake, programe adherence, increase or decrease in BMI, utility gains, which favoured the intervention. **Authors conclusions** Intervention (Commercial Program) was cost-effetive from a health funder and societal perspective. **Additional notes** *Funding/conflict of interest:* Authors have received grants from numerous companies in various industries (pharmaceuticals, nutritions, weight watchers, coca-cola, Sara Lee).
Karnon 2013	**Design**	**Assumptions and variables** • *Weight assumptions:*	**Key findings** *Base case* *TUFTS:*

	• *Model type:* Risk adjusted cost-effectiveness analysis (propensity weighted regression analyses) • *Intervention:* High level of involvement from the practice nurse • *Comparator:* Low level of involvement from the practice nurse • *Time horizon:* One year **Population** Obese adults (BMI≥30). **Locations, perspective** Australia, Health care payer Primary care	○ *Loss:* Statistically significant difference in change in BMI in favor of the high level model, and non-significant improvements with respect to patients losing any, 5 and 10% of their baseline weight.; ○ *Regain*: Estimated QALY gain was based on assumption that observed weight loss at 12 months would be regained over the next 2 years, returning to expected trajectory without intervention.; ○ *Maintenance:* `- • *Comorbidities:* Comorbidities included in weighted regression models (conditions of mental health, respiratory, musculoskeletal, sleep apnoea, cancer, CHD, GI, heart disease, diabetes,) • *QoL/Utility:* Not used in main analysis. QALYs calculated were only presented in the discussion.; Assumed a linear relationship, a QALY gain of 0.055 per one point decrease in BMI.; (Trueman 2010; Counterweight Project Team 2008) • *Attrition:* Not included. **Outcomes** • $/additional person losing weight • $/person losing 5% weight • $/BMI unit lost *CE threshold:* • *CEAC presented.* • *AUS $2k-10k* • *Discounting:* NA - time horizon was one year. • *Currency, year:* AUD ($), 2010 (year estimated as time of data collection) **Quality rating (TUFTS):** 3	• USD $6700/QALY; *Publication:* • $/additional person losing weight: $6,741 (95%CI: $1223 to low level model dominates) • $/additional unit of BMI lost: $563 (95% CI $123 to $1547) • QALYG per unit decrease in BMI 0.055; $10,132/QALYG • *Sensitivity analyses* Multivariate analyses. **Authors conclusions** Authors conclude increased involvment of practice nurses in clinical activities is assocaited with additonal health benefits that are achieved at a reasonable cost. **Additional notes** *Funding/conflict of interest:* None reported. QALYs gained were included in the discussion of the paper, and not part of the main results presented.
Tsai 2013	**Design**	**Assumptions and variables**	**Key findings**

	• *Model type:* Trial based model • *Intervention:* Brief lifestyle counseling; enhanced lifestyle counseling (enhanced therapy include either mean replacements or weight loss medication, orlistat or sibbutramine) • *Comparator:* Usual care • *Time horizon:* Two years **Population** BMI 30-50kg/m2, weight≤400 pounds, abdominal obesity, and at least one of four criteria for metabolic syndrome. **Locations, perspective** Penssylvania USA, Health care payer Primary care	• *Weight assumptions:* ○ *Loss:* Trial based results: Weight loss was modelled from the trial using a linear mixed effects model.; ○ *Regain*: `-; ○ *Maintenance:* `- • *Comorbidities:* Not included. • *QoL/Utility:* ; ; Trial based EQ-5D-3L • *Attrition:* Attrition for study was not reported. **Outcomes** • $/kg-year of weight loss (kilo-years is used to standardise length of follow up). • $/QALYG *CE threshold:* • *US$ 50K/QALYG* • *US$ 100K/QALYG* • *US$100-$200/kg-year* • *Discounting:* 3% • *Currency, year:* USD ($), 2011 **Quality rating (TUFTS):** 4	*Base case* *TUFTS:* • BLC vs SC: dominated • ELC vs BLC: $40k/QALYG • ELC vs SC: $120K/QALYG • No. sig diff. in QALYs between groups.; *Publication:* • Brief counseling: Less than $20,000/QALY over 10-year period • Enhanced counseling: Less than $44,000/QALY over 10-year period • *Sensitivity analyses* Univariate, multivariate and probabalistic analyses. 95% CI were undefined in base case (bootstrapping). **Authors conclusions** Based on $/QALY, authors conclude the interventions were not cost-effective relative to usual care, but could be cost-effective over the long term (>10 years). **Additional notes** *Funding/conflict of interest:* Funded by Government Enhanced lifestyle counseling included treatment with weightloss medication.
Finkelstein 2014	**Design** • *Model type:* Multivariate regression model • *Intervention:* Qsyma (phentermine and topiramate) and lifestyle (weight watchers, Vtrim program, Jenny craig ave. income food substitution, Jenny Craig high	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* One year on treatment; benefits linearly decay to zero from year 2 through to 4.; ○ *Regain*: Not modelled.; ○ *Maintenance:* Not modelled. • *Comorbidities:* Not modelled.	**Key findings** *Base case* *TUFTS:* • 2 programs (excluding pharmaceutical treatments): ICERS WW vs low-cost/low intensity intevention: $35k/QALY; • Vtrim program vs WW program: $100k/QALY;

	income food substitution) [other pharmaceutical interventions reviewed but not included in this table] • *Comparator:* Control: lifestyle (low cost/low intensity intervention) • *Time horizon:* 5 years **Population** Adults with BMI<40kg/m2 **Locations, perspective** USA, Payer perspective. Primary care	• *QoL/Utility:* ; Multivariate linear regression model was constructed to assess the impact of weight loss on change in QoL. • Independent variables: weight loss, weight loss squared, gender, age, baseline BMI, and baseline QALY. • Dependent variable: change in QoL at 1 yea; Trial based SF-12. • *Attrition:* No other items modelled. Authors intentionally reduced the number of assumptions to provide a straightforward comparison of commerically available treatments. **Outcomes** • $/kg of weight lost • $/QALY gained *CE threshold:* • *US$ 50K* • *Discounting:* Not applied. • *Currency, year:* USD ($), 2013 **Quality rating (TUFTS):** 5	*Publication:* • $34,630/QALYG for weightwatchers compared with control. • *Sensitivity analyses* Univariate, multivariate and probabalistic analyses. Univariate (benefits declining after medication ceases; effectiveness based on QoL; cost of medications; discount rates, time horizon shortened). Model was sensitivie to all these parameters. PSA: 95% of simulations are below 80k/QALY. **Authors conclusions** All other interventions were prohibitively expensive or inferior in that weight loss could be achieved through lower costs. **Additional notes** *Funding/conflict of interest:* Funding from industry (pharmaceutical, medical devices, Jenny Craig, and Weight Watchers) Benefits from trials with duration of at least 1 year are extropolated to 5 years.

Fuller 2014	**Design**
	• *Model type:* Markov model
	• *Intervention:* weight loss program by commerical provider (weight watchers) (12 months)
	• *Comparator:* Standard care defined by National Guidelines
	• *Time horizon:* Lifetime (until death or age 99)
		Assumptions and variables
		• *Weight assumptions:*
		  ○ *Loss:* Costs and outcomes extrapolated from 2 years to lifetime.;
		  ○ *Regain*: Trial based results at the end of Year 2.
		  ○ CP: 0.09 BMI point per month after Year 1
		  ○ SC: 0.03 BMI point per month after Year 1;
		  ○ *Maintenance:*
		• *Comorbidities:* T2DM
			Key findings
			Base case
			TUFTS:
			• Not in TUFTs;
			Publication:
			• Commerical program was a dominant strategy. (95% CI: dominant to $6225/QALYG)
			
			• *Sensitivity analyses*

	Population Adults (≥18 years) with BMI 27-35kg/m2. **Locations, perspective** Australia, health care funder This study is follow on from Fuller 2013. Perspective is not explicitly stated but previous study incorporated Australia, UK and Germany. Primary care	• *QoL/Utility:* ; ; In trial: Impact of Weight on Quality of Life Questionnaire-Lite (IWQOL-Lite) (Kolotkin 2001; Mueller 2011). Utility was derived using algorithm to SF-6D (Brazier 2004) • *Attrition:* **Outcomes** • $/QALY gained *CE threshold:* • *AUS: $50k/QALYG* • *Discounting:* 3.5% • *Currency, year:* **Quality rating (TUFTS):** Not in TUFTs	**Authors conclusions** Referral to community based interventions may provide a highly cost-effective approach. **Additional notes** *Funding/conflict of interest:* uthors have received grants from numerous companies in various industries (pharmaceuticals, nutritions, weight watchers, coca-cola, Sara Lee).
Lewis 2014	**Design** • *Model type:* • *Intervention:* Very low calorie diet replacement weight reduction program. • *Comparator:* BMI ≥ 30kg/m2: • Weight watchers, Counterweight and slimming world. • BMI ≥ 40kg/m2: no treatment, gastric banding and gastric bypass. • *Time horizon:* 10 years **Population** Two groups: BMI ≥ 30kg/m2 BMI ≥ 40kg/m2 **Locations, perspective**	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Change in BMI over time were modelled using trial based data. ○ Observational trial reported a reduction of ~8kg/m2 in BMI (≥30kg/m2) and ~13kg/m2 in BMI (≥40kg/m2).; ○ *Regain*: BMI of intervention group linearly increases to level of natural gain (no treatment) group (from Year 1 to ~Year 4).; ○ *Maintenance:* • *Comorbidities:* Diabetes, CHD and colorectal cancer. • *QoL/Utility:* ; Study (Macran 2004) assessed the relationship between BMI and utility scores.; EQ-5D sourced from literature (Macran 2004) • *Attrition:* • Effectiveness data used: 88% of participants were engaged in program after 12 months, subseqeuntly 30% discontinued annually.	**Key findings** *Base case* *TUFTS:* • Not in TUFTs; *Publication:* • $/QALY: • BMI ≥ 30kg/m2: intervention vs various comparators - £11,895, £12,453, £12,585 and £12,233 • BMI ≥ 40kg/m2: intervention vs no treatment, £4356 • [gastric banding and bypass were dominant stragies] • *Sensitivity analyses* Scenario analysis: assuming people without 12 mnth data avialable have no reduction in baseline BMI. **Authors conclusions**

	England, Health care payer (NHS) Community	• BMI data were excluded from participants that made more than one attempt at the weight loss phase of the program. **Outcomes** • \$/QALY gained *CE threshold:* • *£20K-30K/QALY* • *Discounting:* 3.5% • *Currency, year:* **Quality rating (TUFTS):** Not in TUFTs	VLCD is cost-effective compared with weightwatchers, cotunerweight, and slimming world in people with BMI≥30kg/m2. However, VCLD is not cost-effective compared with bariatric surgery and bypass in people with BMI≥40kg/m2 **Additional notes** *Funding/conflict of interest:* Funded by sponsor Data on participants that dropped out were not collected, and model was based on compliant participants biasing the results in favour of the intervention. The authors noted that the assessment of CE of single entry into the program was the question to be
Meads 2014	**Design** • *Model type:* Markov model • *Intervention:* Referral to commercial weight loss program (12 weeks) • *Comparator:* Usual care i.e. no active component • *Time horizon:* Lifetime **Population** Mean cohort age: 47 years, BMI 36.8 kg/m2. **Locations, perspective** UK, Health care payer Primary care	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* ; ○ *Regain*: Weight was regained at a constant annual rate after year 1 in both arms. ○ Usual care: 0-12months weight was maintained. ○ Intervention: weight loss 0-12 months.; ○ *Maintenance:* • *Comorbidities:* T2DM, stroke and MI • *QoL/Utility:* Additive approach to utility calculations.; ; Based on UK studies using the EQ-5D. • *Attrition:* **Outcomes** • £/QALYG *CE threshold:* • *CEAE presented.* • *GBP £ 20k* • *Discounting:* 3.5%	**Key findings** *Base case* *TUFTS:* • Cost saving; *Publication:* • Favours intevention • After year 1: £6906/QALYG • Lifetime: dominant strategy. • *Sensitivity analyses* Univariate, multivariate and probabalistic analyses. Authors state model was robust to sensitivity analyses. **Authors conclusions** Authors concluded that the 12 week primary care referral to the commerical program was cost effective in the short and long terms. **Additional notes**

		• *Currency, year:* GBP (£) , 2012 **Quality rating (TUFTS):** 5.5	*Funding/conflict of interest:* Funding from Slimming World. Compliance with the commercial program was not considered in the model. Weight gain earlier than 1 year was not considered.

Verhaeghe 2014	**Design**
	• *Model type:* Markov model
	• *Intervention:* health promotion of physical activity and healthy eating program (10 weeks), repeated yearly
	• [follow up data 6 months after int.]
	• *Comparator:* Treatment as usual (does not give a description of what this comprises).
	• *Time horizon:* Lifetime
	
	Population
	Individuals living in sheltered housing.
	
	Locations, perspective
	Belgium (limited societal)
	Community
		Assumptions and variables
		• *Weight assumptions:*
		  ○ *Loss:* A reduction of one BMI results in a decreased risk of obesity related comorbidity.;
		  ○ *Regain*: ;
		  ○ *Maintenance:*
		• *Comorbidities:* T2D, CHD, stroke, colon cancer [mutally exclusive health states]
		• *QoL/Utility:* ; QoL was applied to disease states.; De Smedt et al 2012
		• *Attrition:* Compliance modelled in sensitivity
		
		Outcomes
		• $/QALY gained
		CE threshold:
		• *€30K/QALY*
		• *Discounting:* Costs: 3%
		• QALY: 1.5%
		• *Currency, year:* EUR (€), 2011
		
		Quality rating (TUFTS): 5.5
			Key findings
			Base case
			TUFTS:
			• US$ 33,000/QALY;
			Publication:
			• 20 years
			• Men: €27,096/QALY)
			• Women: €40,139/QALY
			
			• *Sensitivity analyses*
			Univariate, scenario/multivariate, and PSA sensitivity analyses conduted. PSA showed sensitivity to intervention effect and RR in reducing diabetes.
			1) full compliance to program (reduced ICER)
			2) Increase HRQoL (reduced ICER)
			3) Offering program twice yearly (increased ICER)
			4) Reducing time horizon (increased ICER)
			
			Authors conclusions
			The intervention was cost-effective in men but not women.
			
			Additional notes
			Funding/conflict of interest: Funding from University scholarship.
			Authors note uncertainty of intervention effect and costs has the greatest impact in the model.

Wilson 2015	**Design** • *Model type:* Archimedes model (does not used state to state transitions) • *Intervention:* 12 week community based weight control program (follow up to 28 wks after intervention) • *Comparator:* Usual care • *Time horizon:* 20 years **Population** People with mexican origin and low SES **Locations, perspective** USA, societal perspective (authors state this but it is not clear) Community	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Model asssumed weight loss goals of 2% and 5%.; ○ *Regain*: ; ○ *Maintenance:* • *Comorbidities:* • *QoL/Utility:* Disutility weights for diabetes related orders and illnesses; ; Sullivan and Ghushchyan 2006; Coffey et al 2002 • *Attrition:* **Outcomes** • $/QALY gain by goal group and time horizon is presented. *CE threshold:* • *US$ 50K* • *Discounting:* 3% • *Currency, year:* **Quality rating (TUFTS):** In TUFTs but not assessed.	**Key findings** *Base case* *TUFTS:* • In TUFTs but not assessed.; *Publication:* • 20 years • weight loss 2%: $57,430/QALY gained • weight loss 5%: $61,893/QALY gained • *Sensitivity analyses* Univariate sensitivity analyses were conducted on the time horizon, initial weight group. The model was senstive to these parameters. The ICER increased when time horizon was reduced. **Authors conclusions** Authors concluded intervention can be cost-effective, but the ICER is above the traditional threshold that applied. Intervention is cost effective for morbidly obese participants. **Additional notes** *Funding/conflict of interest:*
Hoerger 2015	**Design** • *Model type:* Markov model [choice of model validated in another paper] • *Intervention:* Medicare Intenstive Behavioural program • [weight loss of >3kg at 6 months leads to more reimbursement of treatment for a further 6 months]	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Usual care: no weight change ○ Intervention: weight loss of 9-16 pounds, if all sessions were attended and full effectiveness of intervention.; ○ *Regain*: Weight was regained at a rate of 0.3 BMI units per year until original weight was reached,; ○ *Maintenance:*	**Key findings** *Base case* *TUFTS:* • Not in TUFTs; *Publication:* • Base case: intervention is cost saving. • One way sensitivity analyses: range from cost-savings to $28,896/QALY

	• *Comparator:* Usual care • *Time horizon:* Lifetime (until death or age 95) **Population** Medicare beneficiaries with obesity (age>65 year and BMI≥30kg/m2) **Locations, perspective** USA, health care payer Primary care	• *Comorbidities:* Diabetes risk factors are modelled [model excluded people with diabetes or undiagnosed diabetes were excluded, as the intervention claimed to delay diabetes onset.] • Model included diabetes, CHD, and stroke [weight loss reduced risk of complications] • *QoL/Utility:* The direct change in utility from losing weight was similar to that observed in the DPP.; Weight loss improves quality of life.; Ackermann 2009 • *Attrition:* **Outcomes** • $/QALY *CE threshold:* • *$50k/QALYG* • *Discounting:* 3% • *Currency, year:* **Quality rating (TUFTS):** Not in TUFTs	• *Sensitivity analyses* One way sensitivity analyses **Authors conclusions** Intervention is cost saving. **Additional notes** *Funding/conflict of interest:* Funded by Government Authors note intervention is less cost effective in primary care settings or if fewer interventions sessions are supplied by providers or used by participants. The effectiveness of the lifestyle intervention, the pattern of implementation and utilization
McRobbie 2016	**Design** • *Model type:* Trial based model • *Intervention:* Weight Action Programme (WAP) • *Comparator:* Best practice nurse led intervention • *Time horizon:* One year **Population** Aged ≥ 18 years; BMI ≥ 30 or BMI ≥ 28 with comorbidities. **Locations, perspective**	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Weight and BMI are not explicitly modelled.; ○ *Regain*: `-; ○ *Maintenance:* `- • *Comorbidities:* Assumed that the prior history of healthcare use did not influence the model. • *QoL/Utility:* Regression analysis conducted controlling for differences in baseline utility score [between groups was 0.011] and age.; EQ-5D-5L; Within trial • *Attrition:* Assumed that the cost of WAP attendance of 15 participants for all sessions.	**Key findings** *Base case* *TUFTS:* • Not in TUFTs; *Publication:* • £7742 per QALY gained • *Sensitivity analyses* CEAC are presented. Sensitivity analyses: 1) Total cost of WAP (increases ICER with increasing cost)

	UK, Health care payer (NHS) Primary care (delivered by research health psychologists)	**Outcomes** • $/QALY *CE threshold:* • *£20K–30K/QALYG* • *Discounting:* NA - time horizon was one year. • *Currency, year:* **Quality rating (TUFTS):** Not in TUFTs	2) WAP staffing costs (ICER increases with NHS staff band/competency level) 3) Proportion of attendance during session and maintenance (ICER increases as number of attendances decrease - most sensitive) **Authors conclusions** Although both treatments are cost-effective based on threshold, the intervention is cost effective compared with usual care. Further attaned needs to be give to increasing retention rates. **Additional notes** *Funding/conflict of interest:* Funded by Government
Smith 2016	**Design** • *Model type:* Markov model • *Intervention:* Online adaptation of the diabetes prevention program(ODPP) • lifestyle intervention [one year] • *Comparator:* Usual care • *Time horizon:* 10 years **Population** Obses/overweight cohort. **Locations, perspective** USA, two persepectives presented: health care payer and societal.	**Assumptions and variables** • *Weight assumptions:* ○ *Loss:* Probabilities of the amount of weight lost were trial based results. ○ [After 12 months 50 ODPP patients lost 4.94kg.]; ○ *Regain*: ; ○ *Maintenance:* • *Comorbidities:* Diabetes (none, stable or complicated) • *QoL/Utility:* Utilities were linked to diabetes health states. Each health state's utility was multiplied by time in that state, then summed across all states and all time in the model.; ; Smith et al 2010; Herman et al 2005. • *Attrition:* [Need to check original trial for attrition] **Outcomes** • $/QALY • $/case averted *CE threshold:*	**Key findings** *Base case* *TUFTS:* • In TUFTs but not assessed.; *Publication:* • Health care payer: $14,351/QALY gained • Societal: $29,331/QALY gained • *Sensitivity analyses* Univariate, multivariate and probabalistic analyses. Authors note results were robust with sensitivity analyses. One way sensitivity analyses presented. Model was most sensitive to annual probability of developing stable diabetes. No sensitivity analyses were conducted on probability of weight change status. In probabilistic sensitivity analyses, ODPP was cost-effective in 20–58% of model iterations using an acceptability threshold of $20,000, 73–92% at

		• *$100K/QALY* • *Discounting:* 3% • *Currency, year:* **Quality rating (TUFTS):** In TUFTs but not assessed.	$50,000, and 95–99% at $100,000 per QALY gained **Authors conclusions** ODPP may offer an economical approach to combating overweight and obesity. **Additional notes** *Funding/conflict of interest:* Funded by Government

8.5 Appendix 5 - Obesity and quality-of-life literature search

Searches were conducted in PubMed (Medline and PreMedline) and EMBASE electronic databases to identify any relevant journal articles. All searches were conducted from 1990 until present (Jan 31, 2017) and results were limited to articles published in English. All abstracts were reviewed for relevant articles and only included if conducted in human subjects, an adult population, English full text papers and did not include trials that evaluated BMI post intervention. Additional references were identified by hand-searching the bibliographies of all retrieved publications of those articles that met the inclusion criteria.

Database: Embase <1974 to 2017 January 31>, Ovid MEDLINE(R) Epub Ahead of Print, In-Process & Other Non-Indexed Citations, Ovid MEDLINE(R) Daily and Ovid MEDLINE(R) <1946 to Present>
Search Strategy:

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1 *obesity/ or *overweight/ or (obesity or overweight or obese).ti,ab. (632774)

2 *quality of life/ or ((quality adj life) or qol or qaly or qalys or sf-6d or sf 6d or sf6d or eq-5d or eq 5d or eq5d or sf-36 or sf 36 or sf36 or hui or aqol).ti,ab. (250613)

3 1 and 2 (6092)

4 limit 3 to yr="2015 -Current" (1480)

5 (editorial or erratum or letter or note or comment or commentary or conference abstract).pt. (6329869)

6 4 not 5 (1060)

7 remove duplicates from 6 (698)

8 limit 7 to (adult <18 to 64 years> or aged <65+ years>) [Limit not valid in Ovid MEDLINE(R),Ovid MEDLINE(R) Daily Update,Ovid MEDLINE(R) In-Process,Ovid MEDLINE(R) Publisher; records were retained] (559)

9 limit 8 to "all adult (19 plus years)" [Limit not valid in Embase; records were retained] (427)

10 from 9 keep 1,3,8-10,15,18,22,28,32-33,36,39,42,45,49,52-54,57,60,67,73-74,77,84,93,95,106,111,116,125,127,129-130,133,139,141,149,159,161-162,170-172,175,180-181,184-185,195-196,198,206,210,216,219,222,228-229,231,253,329,335,357,364,367 (67)

11 from 9 keep 20,27,66,75,78,92,114,118,143,152,154,157-158,163,165-166,178,189-191,193,200,204,225,227,232-234,238-240,245-247,252,256-257,259,267-268,274,280-281,284-285,295-296,347,372,375-378,380-381,383,387-391,394,397,400,403-404,408-409,411-412,414,422-426 (76)

12 from 9 keep 306-307,314,320,322-323 (6)

13 10 or 11 or 12 (149)

8.6 Appendix 6 - HILDA Wave 1 Characteristics

Selected Wave 1 Individual Sample Characteristics Compared with Population Estimates from the ABS Monthly Population Survey (persons aged 15 years or over)

Wave 1			
Area of usual residence	21.5	16.9**	18.0**
Sydney			
Rest of NSW	12.2	14.5**	14.1**
Melbourne	18.4	17.3*	17.5
Rest of Victoria	6.7	7.5	7.3
Brisbane	8.6	8.8	8.8
Rest of Queensland	10.0	11.5*	11.4
Adelaide	5.8	6.1	5.8
Rest of South Australia	2.0	2.4*	2.3
Perth	7.3	7.5	7.4
Rest of Western Australia	2.5	2.8	2.7
Tasmania	2.4	2.8	2.7
Northern Territory	0.9	0.5**	0.5**
ACT	1.6	1.6	1.6
Sex			
Male	49.3	47.4**	48.6*
Female	50.7	52.6**	51.4*
Age (years) at 30 Sept 2001			
15-19	8.8	8.7	9.4*
20-24	8.9	7.4**	7.8**
25-34	18.7	18.7	18.7
35-44	19	21.7**	21.4**
45-54	17.1	17.1	17.1
55-64	11.8	12	11.7
65 or over	15.6	14.4*	13.9**
Marital status			
Married (including de facto)	58.7	63.4*	62.7**
Not married	41.3	36.6**	37.3**
Relationship in household			
Family member			
Husband, wife or partner			
with child <15	23.1	26.6**	26.2**
without child <15	36.7	36.3	36
with dependents	28	30.3**	29.9**
without dependents	32	32.7	32.3
Lone parent			
with child <15	3.2	3.6*	3.4
w dep students but w/o children <15	0.6	0.6	0.6
without dependents	1.6	1.4	1.5
Dependent student	6.8	6.2*	5.7**
Non-dependent student	8.4	6.2**	8.1
Other family member	2.3	2.1	2.4
Non-family person			
Lone person	11.9	14.0**	12.9*
Not living alone	5.3	3.0**	3.3**
Indigenous status			
Indigenous	1.7	1.8	
Non-indigenous	98.3	98.2	
Birthplace			

Born in Australia	72.4	74.4**	
Born outside Australia			
Main English-speaking country	10.2	10.9	
Other country	17.5	14.7**	
Labour force status			
Employed			
Full-time	42.1	41.7	
Part-time	17.4	19.5**	
Unemployed	4.3	4.4	
Not in the labour force	36.3	34.5*	
Employment status in main job			
(employed persons only)			
Employee	86.0	87.0	
Employer	3.6	3.9	
Own account worker	10.0	8.4**	
Contributing family worker	0.4	0.8**	

Source: Table 2, Watson, 2002.

Notes: ** and * denotes significantly different from the ABS population estimate at the 99% and 95% confidence levels respectively.

a With the exception of indigenous status and employment status, the ABS estimates come from the Monthly Population Survey for October 2001. In the case of the two exceptions, data for August 2001 are used. With the exception of country of birth and relationship in household, the population that these estimates apply to is all civilians aged 15 years and over. The figures for country of birth and relationship in household exclude persons living in an institution.

b The HILDA estimates are also for people aged 15 years and over, but include defence force personnel and exclude people living in remote areas of Australia and those living in special dwellings. They have also been adjusted to account for variation in the probability of selection.

c We vary from the usual ABS definition in defining full-time work solely on the basis of usual hours worked (rather than on a combination of usual hours and actual hours worked)

8.7 Appendix 7 - SF-36 Summary Scores

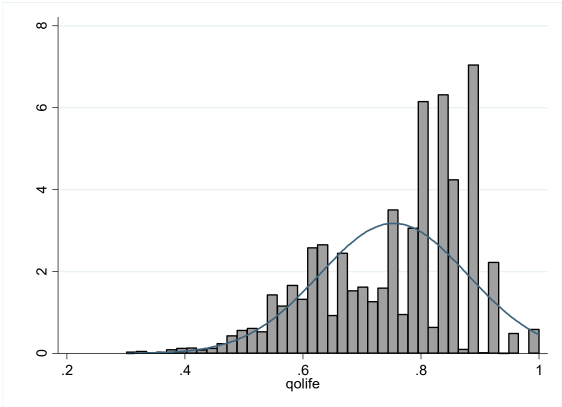
```
THE NATIONAL HEALTH SURVEY POPULATION NORMS (1995)

***********************************************************
* MEAN AND SD FROM AUSTRALIAN ADULT POPULATION *
* THE NATIONAL HEALTH SURVEY: SF-36 POPULATION NORMS 1995 *
***********************************************************/

gen PF_ZC=(SF_PF-83.46290)/23.22864
gen RP_ZC=(SF_RP-80.28166)/34.83783
gen BP_ZC=(SF_BP-76.94163)/24.83714
gen GH_ZC=(SF_GH-71.81575)/20.35165
gen VT_ZC=(SF_VT-64.47694)/19.77187
gen SF_ZC=(SF_SF-85.05929)/22.29047
gen RE_ZC=(SF_RE-83.19165)/32.15215
gen MH_ZC=(SF_MH-75.97772)/16.96210


*guide says only to do so if all 8 are not missing
gen prawc = (PF_ZC * 0.47268)+ (RP_ZC * 0.38210) + (BP_ZC * 0.36750)
+ (GH_ZC * 0.18993) + (VT_ZC * -0.01883) + (SF_ZC * -0.01324) +
(RE_ZC * -0.14971) + (MH_ZC * -0.27145)
gen mrawc = (PF_ZC * -0.24358)+ (RP_ZC * -0.13410) + (BP_ZC * -
0.12414) +(GH_ZC * 0.05271) + (VT_ZC * 0.27100) + (SF_ZC * 0.26460)
+ (RE_ZC *0.35922) + (MH_ZC * 0.48753)

gen PCS_ABS = (prawc*10) + 50
gen MCS_ABS = (mrawc*10) + 50
```

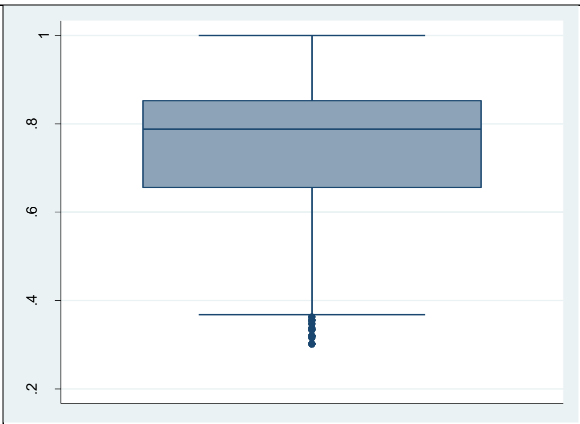
Source: Australian Longitudinal Study on Women's Health
http://www.alswh.org.au/images/content/pdf/InfoData/Data_Dictionary_Supplement/DDSSection2SF36.pdf

8.8 Appendix 8 - Tests for normality

The histogram of QoL scores (with a normal distribution overlayed) shows a higher proportion of respondents with high SF-6D scores and skewed to the left. In the box blot, the dark line in the box is the median SF-6D value. The box plot is not symmetrical (the median and mean are not located at the same point), the 'whiskers' are not equivalent (the 25th and 75th percentiles are not symmetric) and there are outliers outside of the interquartile range. These extreme values are pulling the median, indicating a skew to the left. This would indicate that the SF-6D variable is not distributed normally.

Tests for normality in the QoL (SF-6D) data





8.9 Appendix 9 – BMI change groups (wave 6 to 15) – Sensitivity Analysis

	SA1		SA2	
	β	se	β	se
Normal to overweight	-0.007	0.004	-0.002	0.005
Normal to obese	-0.026**	0.010	-0.025*	0.012
Overweight to normal weight	-0.017**	0.006	-0.005	0.007
Remain overweight	-0.009**	0.003	-0.006	0.004
Overweight to obese	-0.022***	0.005	-0.018**	0.006
Obese to normal weight	-0.014	0.015	0.019	0.021
Remain obese	-0.006	0.007	0.017*	0.008
Obese to overweight	-0.024***	0.004	-0.010*	0.004
Age 18-24	-0.011	0.012	-0.017	0.015
Age 24-34	0.003	0.004	-0.004	0.005
Age 45-54	0.002	0.004	0.001	0.005
Age 55-64	-0.001	0.004	0.003	0.005
Age 65-74	0.01	0.005	0.002	0.006
Age 75+	-0.001	0.007	-0.033***	0.008
Year 12/certificate/diploma	0.001	0.003	-0.002	0.003
Year 11 and below	0.000	0.004	0.004	0.004
OECD income 1	-0.014**	0.005	0.005	0.005
OECD income 2	0.000	0.004	0.006	0.005
OECD income 3	0.001	0.004	0.006	0.004
OECD income 5	0.005	0.004	-0.002	0.004
Self-employed	-0.001	0.004	0.005	0.005
Unemployed	-0.021*	0.009	-0.021	0.011
Unpaid housework	-0.025***	0.006	-0.009	0.007
Retired	-0.011*	0.005	-0.001	0.006
Student	-0.022	0.017	-0.009	0.023
Other	-0.048***	0.006	-0.025**	0.008
Non- metro area	0.001	0.004	0.001	0.004
Separated/divorced/widowed	-0.015***	0.003	0.004	0.004
Single	-0.008	0.004	0.005	0.005
LTHC – no limitations	-0.122***	0.004	-0.037***	0.004
LTHC – limits work	-0.039***	0.005	-0.015**	0.005
LTHC- can't work	-0.167***	0.012	-0.053**	0.017
Smoker	-0.007***	0.002	0.000	0.002
Previous smoker	0.002	0.003	0.002	0.003
Non-drinker	0.011**	0.004	0.006	0.005
Drinker	0.015***	0.004	0.003	0.004
No Activity	-0.049***	0.005	-0.025***	0.005
Activity 3 + times/week	-0.014***	0.003	-0.002	0.004
Activity everyday	0.024***	0.003	0.011***	0.003
_cons	0.806***	0.006	-0.009	0.007
N	6753		6481	
R^2	0.367		0.058	
LL	6105.04		4974.97	
AIC	12130.08		-9869.94	
BIC	11857.37		-9598.87	

8.10 Appendix 10 – Percentage of body weight groups – Sensitivity analysis

	Heavy Weight Gain	Heavy Weight Loss	Weight Loss	Weight gain	Stable weight	Full model	
	β	β	β	β	β	Males	Females
BMI	-0.006***	-0.002	-0.005***	-0.008***	-0.008***		
Male	0.115***	-0.005	0.041**	0.103***	0.068***		
Heavy weight gain						-0.031**	-0.074***
Heavy weight losss						-0.055***	0.007
Weight loss						-0.027**	-0.012
Weight gain						-0.000	-0.041***
Age 18-24	0.018	-0.002	0.03	0.082***	0.030*	0.092***	0.027
Age 24-34	-0.04	0.041	0.027	0.042*	0.007	0.043***	0.003
Age 45-54	-0.009	-0.049	-0.042	-0.03	-0.057***	-0.052***	-0.046***
Age 55-64	0.014	-0.049	-0.036	0.004	-0.052***	-0.052***	-0.045***
Age 65-74	0.034	-0.07	0.024	0.009	-0.029*	-0.047**	-0.024
Age 75+	-0.047	-0.125*	-0.027	-0.044	-0.103***	-0.117***	-0.092***
Year12/cert/diploma	-0.016	-0.033	-0.013	0.03	-0.005	-0.034**	-0.012
Year11 and below	-0.004	-0.011	-0.022	0.03	-0.006	-0.063***	-0.023
OECD income 1	-0.083**	-0.093**	-0.105***	-0.070***	-0.071***	-0.059***	-0.061***
OECD income 2	-0.007	-0.059	-0.041	-0.024	-0.044***	-0.034***	-0.036***
OECD income 3	0.001	-0.013	-0.012	0.002	-0.019**	-0.005	-0.022**
OECD income 5	-0.007	0.026	0.007	0.037*	0.021**	0.026**	0.012
Self-employed	-0.092**	-0.007	0.000	0.003	-0.020*	-0.021	-0.013
Unemployed	-0.068	-0.100	-0.085*	-0.053	-0.084***	-0.096***	-0.040**
Unpaid housework	-0.102***	-0.072*	-0.065*	-0.090***	-0.076***	-0.124***	-0.075***
Retired	-0.103**	-0.027	-0.078**	-0.069**	-0.093***	-0.102***	-0.081***
Student	-0.067	-0.018	-0.019	-0.029	-0.070***	-0.055*	-0.028
Other	-0.198***	-0.194***	-0.178***	-0.209***	-0.186***	-0.197***	-0.161***
Non- metro area	-0.006	0.008	-0.01	0.036*	0.010	0.011	0.007
Separated/div/wid	-0.047*	-0.102***	-0.040*	-0.052**	-0.066***	-0.061***	-0.068***
Single	0.015	-0.034	-0.080***	-0.062***	-0.039***	-0.034**	-0.029*
LTHC-no limitations	-0.645***	-0.623***	-0.600***	-0.565***	-0.429***	-0.407***	-0.406***
LTHC-limits work	-0.272***	-0.207***	-0.216***	-0.231***	-0.137***	-0.125***	-0.147***
LTHC-can't work	-0.738***	-0.715***	-0.694***	-0.719***	-0.532***	-0.503***	-0.493***
Smoker	-0.037***	-0.047***	-0.054***	-0.040***	-0.046***	-0.039***	-0.040***
Previous smoker	0.019	0.038	0.006	-0.012	-0.004	-0.014	-0.007
Non-drinker	0.062**	0.080**	0.085***	0.021	0.055***	0.044***	0.062***
Drinker	0.074***	0.079**	0.113***	0.050**	0.090***	0.079***	0.096***
No Activity	-0.244***	-0.249***	-0.211***	-0.224***	-0.175***	-0.183***	-0.175***
Activity 3+ times/wk	-0.099***	-0.136***	-0.086***	-0.119***	-0.080***	-0.090***	-0.079***
Activity everyday	0.087***	0.143***	0.139***	0.086***	0.103***	0.095***	0.106***
_cons	1.496***	1.466***	1.506***	1.535***	1.587***	1.437***	1.336***
N	5361	3749	7796	10363	63729	43389	49001

8.11 Appendix 11 - Instrumental variable sensitivity analysis

	Model 4		SA1		SA2	
	(1 year lag, all stressful life events)		(5 year lag, all stressful life events)		(Subset of stressful life events)	
	coef	se	coef	se	coef	se
Obesity Predicted Model						
Depression score ≤52	0.062*	0.027	0.038	0.024	0.058*	0.027
Male	0.038	0.020	0.038	0.020	0.038	0.020
Age 18-24	-0.446***	0.034	-0.446***	0.034	-0.446***	0.034
Age 25-34	-0.189***	0.026	-0.189***	0.026	-0.189***	0.026
Age 45-54	0.027	0.025	0.027	0.025	0.027	0.025
Age 55-64	0.034	0.030	0.033	0.030	0.034	0.030
Age 65-74	-0.098**	0.038	-0.101**	0.038	-0.098**	0.038
Age 75+	-0.580***	0.049	-0.584***	0.049	-0.581***	0.049
Year 12, cert or diploma	0.273***	0.026	0.273***	0.026	0.273***	0.026
Year 11 or below	0.403***	0.030	0.403***	0.030	0.403***	0.030
Sep/divorced/widow	0.016	0.025	0.017	0.025	0.016	0.025
Single	-0.050	0.028	-0.049	0.028	-0.05	0.028
OECD income 1st decile	-0.014	0.024	-0.013	0.024	-0.014	0.024
OECD income 2nd decile	0.017	0.019	0.017	0.019	0.017	0.019
OECD income 4rd decile	0.025	0.030	0.025	0.019	0.025	0.019
OECD income 5rd decile	-0.040	0.019	-0.04	0.024	-0.04	0.024
Rural area	-0.105***	0.027	-0.105***	0.027	-0.105***	0.027
Self-employed	-0.101***	0.032	-0.101***	0.030	-0.101***	0.030
Unemployed	0.063*	0.024	0.066*	0.032	0.064*	0.032
Unpaid housework	-0.002	0.030	-0.001	0.030	-0.002	0.030
Retired	-0.051	0.032	-0.05	0.032	-0.051	0.032
Student	-0.167***	0.049	-0.166***	0.049	-0.167***	0.049
Other	-0.026	0.031	-0.024	0.031	-0.026	0.031
LTCondition limits work	0.290***	0.021	0.294***	0.022	0.291***	0.022
LTCondition nolimitations	0.225***	0.020	0.226***	0.020	0.225***	0.020
LTCondition can't work	0.261***	0.051	0.266***	0.051	0.262***	0.051
Smoker	-0.105***	0.023	-0.104***	0.023	-0.105***	0.023
Drinker	-0.183***	0.018	-0.184***	0.018	-0.183***	0.018
None or less than weekly	-0.168***	0.022	0.170***	0.022	0.169***	0.022
1-2 times a week	0.149***	0.016	0.150***	0.016	0.149***	0.016
Every day	-0.236***	0.015	-0.236***	0.015	-0.236***	0.015
_cons	-0.684***	0.042	-0.682***	0.042	-0.684***	0.042
Depression: Reduced Model						
Recent stressful life event	0.194***	0.012	0.056**	0.016	0.252***	0.013
Previous stressful life events	0.082***	0.012	-0.024	0.018	0.110***	0.014
Male	-0.033	0.020	-0.009	0.022	-0.027	0.020
Age 18-24	0.001	0.033	0.062*	0.038	0.009	0.033
Age 25-34	-0.059*	0.026	-0.098***	0.030	0.065*	0.026
Age 45-54	-0.089***	0.026	-0.311***	0.029	-0.091***	0.026
Age 55-64	-0.325***	0.032	-0.594***	0.035	-0.320***	0.032
Age 65-74	-0.587***	0.043	-0.794***	0.047	-0.584***	0.043
Age 75+	-0.792***	0.052	0.044	0.056	-0.790***	0.052
Year 12, cert or diploma	0.023	0.024	0.102**	0.026	0.03	0.024
Year 11 or below	0.078**	0.029	0.171***	0.032	0.092**	0.029
Sep/divorced/widow	0.167***	0.025	0.217***	0.027	0.177***	0.025
Single	0.201**	0.027	0.075**	0.030	0.210***	0.027
OECD income 1st decile	0.093***	0.026	-0.009	0.029	0.090***	0.026
OECD income 2nd decile	0.004	0.021	-0.046	0.024	0.004	0.021

OECD income 4rd decile	0.048*	0.024	-0.103***	0.024	-0.049*	0.021
OECD income 5rd decile	-0.097***	0.025	0.048	0.028	-0.099***	0.025
Rural area	0.059*	0.029	-0.061	0.031	0.058*	0.029
Self-employed	-0.056	0.030	0.353***	0.033	-0.055	0.030
Unemployed	0.339***	0.035	0.129***	0.040	0.352***	0.035
Unpaid housework	0.126***	0.030	0.146***	0.035	0.128***	0.030
Retired	0.121***	0.037	0.219***	0.039	0.134***	0.037
Student	0.189***	0.052	0.309***	0.060	0.180***	0.052
Other	0.305***	0.032	0.621***	0.036	0.299***	0.032
LTCondition limits work	0.632***	0.021	0.323***	0.023	0.611***	0.021
LTCondition no limitations	0.321***	0.024	0.736***	0.026	0.314***	0.024
LTCondition can't work	0.764***	0.057	0.163***	0.064	0.734***	0.057
Smoker	0.156***	0.022	-0.113***	0.025	0.158***	0.022
Drinker	-0.118***	0.018	0.371***	0.020	-0.115***	0.018
No activity/< weekly	-0.179***	0.024	0.199***	0.026	0.368***	0.023
Activity 1-2 times a week	-0.372***	0.023	-0.179***	0.020	0.193***	0.018
Activity every day	-0.556***	0.025	-1.516***	0.020	-0.185***	0.018
_cons	-1.137***	0.046	0.056**	0.048	-1.491***	0.043
N	120,297		119,423		120,297	
Rho	-0.043		-0.010		-0.023	
Log-likelihood	-90,246		-83802		-90170	
AIC	180,624		167737		180472	
BIC	181,264		168376		180112	

8.12 Appendix 12 - DCE literature search

Database: Embase <1974 to 2017 January 31>, Ovid MEDLINE(R) Epub Ahead of Print, In-Process & Other Non-Indexed Citations and Ovid MEDLINE(R) 1996 to Daily Update
Search Strategy:
----
1 *obesity/ (201957)
2 (obesity or obese or diet*or overweight).ti,ab. (416095)
3 1 or 2 (452616)
4 (discrete choice* or DCE or conjoint analysis or discrete choice experiment*).ab,ti. (10687)
5 3 and 4 (60)
6 (editorial or erratum or letter or note or comment or commentary or conference abstract).pt. (5159162)
7 5 not 6 (49)
8 remove duplicates from 7 (28)
9 from 8 keep 6,9,12,18 (4)

8.13 Appendix 13 - Survey Engine Pilot Data

Focus group

The focus group was comprised of university researchers (N=25) who provided feedback during an hour-long session where all sections of the survey and DCE were presented and discussed. Particular attention was given to the description of the DCE vignettes as well as the attributes and levels proposed. Initially there was a separate attribute for diet (low calorie diet, low carbohydrate diet, healthy eating), however the feedback from the focus group suggested only one diet level as all diets require a reduction in calories. In the final version diet and exercise were combined into one attribute with 5 levels. Another attribute, reduced risk of obesity-related disease, was included with risk reduction values of 20%, 40% and 60%. The feedback from the focus group recommended associated obesity diseases described rather than risk values. The appearance attribute levels were also changed from "no change in appearance, feel slimmer, feel more athletic" from discussions in the focus group. It was also discussed in the focus group to exclude an attribute involving reductions in life expectancy. Significant changes were made to the DCE vignette based on suggestion from the group that the wording would need to be sensitive to not offend anyone completing the survey.

Convenience sample

The first draft of the survey was completed by a convenience sample (n=10) to provide initial feedback and suggestions for improvement. Minor formatting changes and corrections of errors were made. The DCE section was updated to include the main question at the top of each page of the survey, to enhance comprehension. The number of choice sets respondents would complete was included in the introduction DCE page.

Pilot 1

A total of 104 respondents completed the pilot survey. After reviewing the results of the pilot, a number of changes were made to the DCE:

- A larger number of respondents than expected selected the dominated strategy (9th choice set). To address this issue, changes were made: The intervention, duration of the program, time commitment and weight-loss were held constant between choice options; cardiovascular risk reduction was added to the dominant option, since there were significant preferences for this level based on the pilot data; and lowest cost, higher reward and higher quality of life were also retained in the dominant strategy.

- The levels of the 'cost of program' attribute were changed. Prior to piloting, the highest program cost level was $300 per month (based on individualised personal training). However, the pilot data suggested that this amount was too high because the coefficient was very large and significant. It was felt that this cost would dominate the other results, limiting trade-offs, especially amongst low income individuals. It was decided to change the costs in the experiment to levels of $0, $25, $50 and $100.

Pilot 2

A second pilot was conducted with 101 respondents. After reviewing the results of the second pilot, a number of additional changes were made:

- There was a coding error in the QoL variable, which meant that the mobility level was present twice.

- Within the fractional design,, it was noticed that certain combinations of the four level attributes were not being covered by the design. To address this, a second experiment design was generated using Ngene software. Multiple iterations of the Ngene code were run, as it was found that using cost as a continuous variable (either with main or interaction effects) resulted in unbalanced choice sets, with no choice sets of the extremes levels compared and high proportion of matching cost levels across choices.

Pilot 3

A third pilot was then conducted with the coding errors corrected, using a new Ngene design A further 121 respondents were collected from Pureprofile. The Ngene code is presented below.

NGENE Designs

```
? This is for the DCE survey of obesity interventions

Design
;alts= OptionA, OptionB
;rows=120
;eff = (mnl, wtp (ref1))
;wtp = ref1(b2, b3, b4, b6, b7,b8,b9,b10/b5)

;model:

U(OptionA) =
b1[1.1] +
b2.dummy[0|0|0|0] * prog[0,1,2,3,4] +
b3.dummy[0|0] * dura[0,1,2] +
b4.dummy[0|0] * time[0,1,2] +
b5[0.01] * cost[0,1,2,4] +
```

```
b6.dummy[0|0|0] * weight[0,1,2,3] +
b7.dummy[0|0|0] * risk[0,1,2,3] +
b8.dummy[0|0|0] * appear[0,1,2,3] +
b9.dummy[0|0] * reward[0,1,2] +
b10.dummy[0|0|0] * qol[0,1,2,3] /

U(OptionB) =
b2 * prog +
b3 * dura +
b4 * time +
b5 * cost +
b6 * weight +
b7 * risk +
b8 * appear +
b9 * reward +
b10 * qol
$
```

8.14 Appendix 14 - Socio-demographic questions

Section 1

The following section will ask you questions about you and your background.

1) What is your current age in years?

- 15 - 24 years
- 25 - 34 years
- 35 - 44 years
- 45 - 54 years
- 55 - 64 years
- 65 - 74 years
- 75 + years

2) What is your gender?

- Female
- Male
- Other

3) Where were you born?

- Australia
- New Zealand
- China
- UK
- Germany
- Greece
- Italy
- Lebanon
- Netherlands
- Vietnam
- Other

4) Are you of Aboriginal and/or Torres Strait Islander origin?

- Yes
- No

5) What is the highest level of education you have obtained?

- Year 11 and below
- Year 12
- Certificate (any level including trade certificate)
- Diploma / advanced diploma
- Bachelors or honours degree
- Graduate diploma / certificate
- Post graduate degree (masters or doctorate)

6) Which of the following best describes your current living situation?

- Single, never married

- Married
- Living with a partner
- Divorced
- Separated
- Widowed
- Prefer not to say

7) Before tax and other deductions are taken out, what is the combined yearly income of everyone in your household? (Include wages, investments and government pensions and benefits)

- Negative or zero Income
- $1 - $19,999 per year ($1 - $379 per week)
- $20,000 - $49,999 per year ($380 - $959 per week)
- $50,000 - $79,999 per year ($960 - $1,539 per week)
- $80,000 - $109,999 per year ($1,540 - $2,109 per week)
- $110,000 - $149,999 per year ($2,110 - $2,879 per week)
- $150,000 - $199,999 per year ($2,880 - $3,849 per week)
- $200,000 or more per year ($3,850 or more per week)
- Don’t know
- Prefer not to say

8) What is your current work status?

Full time paid work	Part time paid work
Self-employed	Retired
Disabled/sick	Unpaid work
Studying	Unpaid housework
Unemployed	Other (please specify)

8.15 Appendix 15 - Weight and lifestyle questions

Section 2

The following section will ask you questions about your health, weight, diet and physical activity.

1) In general, would you say your health is?

- ○ Excellent
- ○ Very good
- ○ Good
- ○ Fair
- ○ Poor

2) Do you have any of the following health conditions?
Select all that apply

☐ Arthritis	☐ Asthma
☐ Cancer	☐ Diabetes Type 1
☐ Diabetes Type 2	☐ Chronic obstructive pulmonary disease (COPD) eg. chronic bronchitis or emphysema
☐ Chronic pain	☐ Depression or other mood disorder
☐ Diabetes	☐ Heart disease
☐ High blood pressure or hypertension	☐ No ongoing medical conditions
☐ Other (please specify)	

3) Do you consider yourself to be:

- ○ Acceptable weight
- ○ Underweight
- ○ Overweight

4) How satisfied are you with your current weight?

- ○ Very satisfied
- ○ Satisfied
- ○ Neither satisfied nor dissatisfied
- ○ Dissatisfied
- ○ Very dissatisfied

5) Have you ever been overweight?

- ○ I used to be overweight but I am normal weight now
- ○ I have never been overweight
- ○ I am currently overweight

6) Are you currently trying to lose weight through changes to your diet and/or exercise?

- ○ No
- ○ Yes - Diet

- Yes - Increasing my physical activity
- Yes - Diet and increasing my physical activity

7) In the past year, how often have you dieted to lose weight?

- Never
- Once
- More than once
- Always on a diet

8) Have you ever paid to join a weight loss program in the past? (e.g. Weight Watchers, Bodytrim, Jenny Craig, Michelle Bridges)?

- Yes
- No

9) How often do you do moderate activities or exercise (such as walking, bowling or playing golf) in a week?

- Not at all
- Less than once a week
- 1-2 times a week
- 3-6 times a week
- Every day

10) How often do you do vigorous activities or exercise (such as running, lifting heavy objects or participating in strenuous sports) in a week?

- Not at all
- Less than once a week
- 1-2 times a week
- 3-6 times a week
- Every day

11) Do you smoke cigarettes or any other tobacco products?

- I have never smoked
- I used to smoke but no longer smoke
- I smoke everyday
- I smoke at least weekly (but not daily)
- I smoke less often than weekly

12) Do you drink alcohol?

- I have never drunk alcohol
- I used to drink but no longer drink
- I drink alcohol everyday
- I drink at least weekly (but not daily)
- Yes, but only rarely

13) What is your current height (without shoes, approximate)?

148 cm / 4'10" and under	166 cm / 5'5½"	184 cm / 6'0½"

○ 150 cm / 4'11"	○ 168 cm / 5'6"	○ 186 cm / 6'1"
○ 152 cm / 5'0"	○ 170 cm / 5'7"	○ 188 cm / 6'2"
○ 154 cm / 5'1"	○ 172 cm / 5'8"	○ 190 cm / 6'3"
○ 156 cm / 5'1½"	○ 174 cm / 5'9"	○ 192 cm / 6'4"
○ 158 cm / 5'2"	○ 176 cm / 5'9½"	○ 194 cm / 6'4½"
○ 160 cm / 5'3"	○ 178 cm / 5'10"	○ 196 cm / 6'5"
○ 162 cm / 5'4"	○ 180 cm / 5'11"	○ 198 cm / 6'6"
○ 164 cm / 5'5"	○ 182 cm / 6'0"	○ 200 cm / 6'7" and over

14) What is your current weight (approximate)?

○ 46 kg / 7 st 3 lb and under	○ 72 kg / 11 st 5 lb	○ 98 kg / 15 st 6 lb
○ 48 kg / 7 st 8 lb	○ 74 kg / 11 st 9 lb	○ 100 kg / 15 st 10 lb
○ 50 kg / 7 st 12 lb	○ 76 kg / 11 st 14 lb	○ 102 kg / 16 st 1 lb
○ 52 kg / 8 st 3 lb	○ 78 kg / 12 st 4 lb	○ 104 kg / 16 st 5 lb
○ 54 kg / 8 st 7 lb	○ 80 kg / 12 st 8 lb	○ 106 kg / 16 st 10 lb
○ 56 kg / 8 st 11 lb	○ 82 kg / 12 st 13 lb	○ 108 kg / 17 st 0 lb
○ 58 kg / 9 st 2 lb	○ 84 kg / 13 st 3 lb	○ 110 kg / 17 st 5 lb
○ 60 kg / 9 st 6 lb	○ 86 kg / 13 st 8 lb	○ 112 kg / 17 st 9 lb
○ 62 kg / 9 st 11 lb	○ 88 kg / 13 st 12 lb	○ 114 kg / 17 st 13 lb
○ 64 kg / 10 st 1 lb	○ 90 kg / 14 st 2 lb	○ 116 kg / 18 st 4 lb
○ 66 kg / 10 st 6 lb	○ 92 kg / 14 st 7 lb	○ 118 kg / 18 st 8 lb
○ 68 kg / 10 st 10 lb	○ 94 kg / 14 st 11 lb	○ 120 kg / 18 st 13 lb and over
○ 70 kg / 11 st 0 lb	○ 96 kg / 15 st 2 lb	

8.16 Appendix 16 - Quality-of-life Questionnaire

Section 4

The following section will ask you questions about your current quality of life.

Under each heading, please tick the ONE box that best describes your health TODAY.

MOBILITY
- ◌ I have no problems in walking about
- ◌ I have slight problems in walking about
- ◌ I have moderate problems in walking about
- ◌ I have severe problems in walking about
- ◌ I am unable to walk about

SELF-CARE
- ◌ I have no problems washing or dressing myself
- ◌ I have slight problems washing or dressing myself
- ◌ I have moderate problems washing or dressing myself
- ◌ I have severe problems washing or dressing myself
- ◌ I am unable to wash or dress myself

USUAL ACTIVITIES *(e.g. work, study, housework, family or leisure activity)*
- ◌ I have no problems doing my usual activities
- ◌ I have slight problems doing my usual activities
- ◌ I have moderate problems doing my usual activities
- ◌ I have severe problems doing my usual activities
- ◌ I am unable to do my usual activities

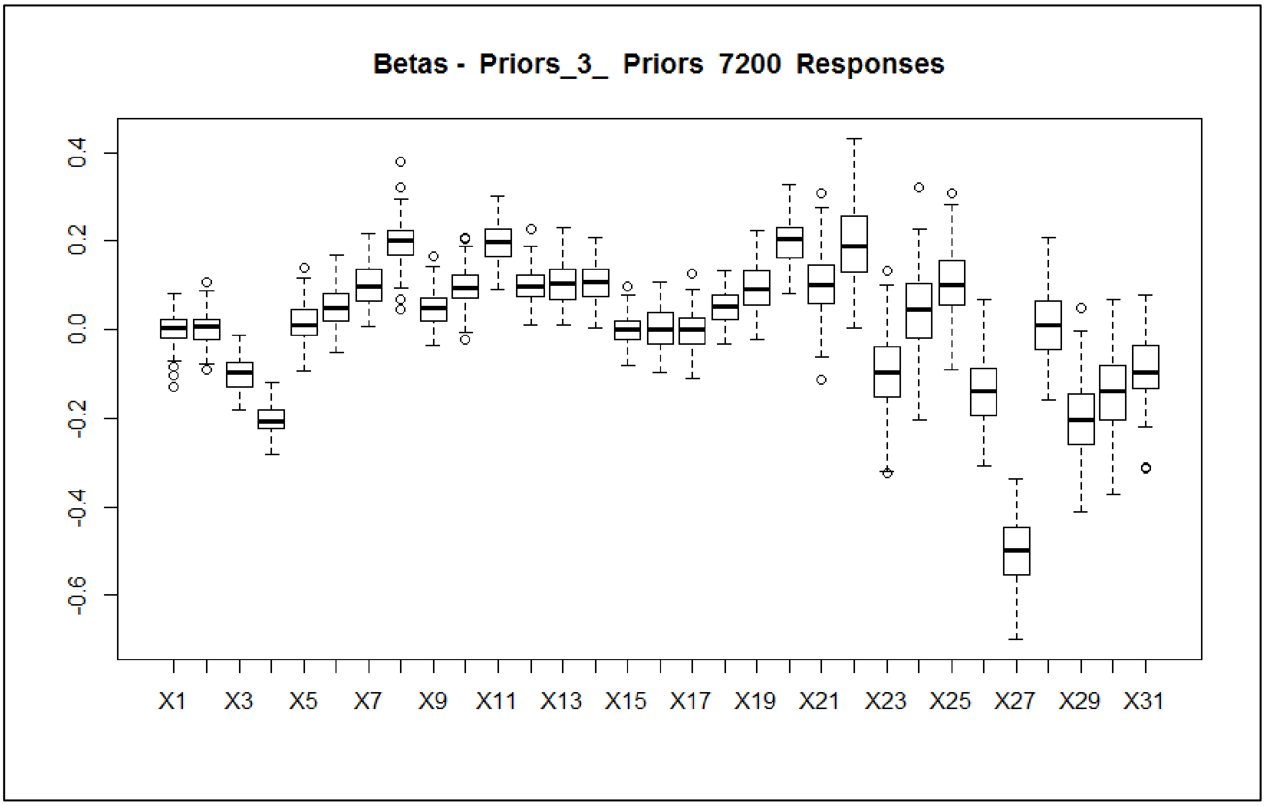
PAIN / DISCOMFORT
- ◌ I have no pain or discomfort
- ◌ I have slight pain or discomfort
- ◌ I have moderate pain or discomfort
- ◌ I have severe pain or discomfort
- ◌ I have extreme pain or discomfort

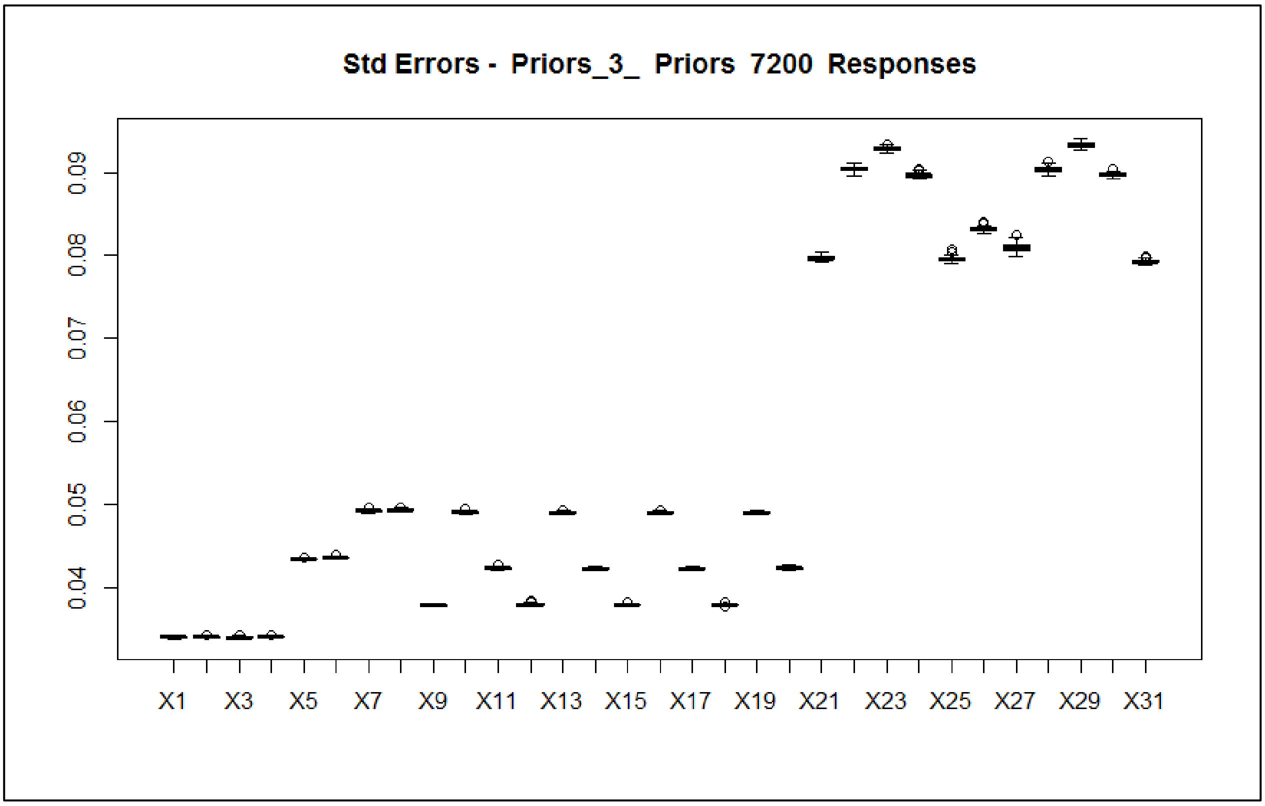
ANXIETY / DEPRESSION
- ◌ I am not anxious or depressed
- ◌ I am slightly anxious or depressed
- ◌ I am moderately anxious or depressed
- ◌ I am severely anxious or depressed
- ◌ I am extremely anxious or depressed

8.17 Appendix 17 - Checklist for conjoint analysis application in health care

1. Was a well-defined research question stated and is conjoint analysis an appropriate method for answering it?
1.1 Were a well-defined research question and a testable hypothesis articulated?
1.2 Was the study perspective described, and was the study placed in a particular decision-making or policy context?
1.3 What is the rationale for using conjoint analysis to answer the research question?
2. Was the choice of attributes and levels supported by evidence? f
2.1 Was attribute identification supported by evidence (literature reviews, focus groups, or other scientific methods)?
2.2 Was attribute selection justified and consistent with theory?
2.3 Was level selection for each attribute justified by the evidence and consistent with the study perspective and hypothesis?
3. Was the construction of tasks appropriate?
3.1 Was the number of attributes in each conjoint task justified (that is, full or partial profile)?
3.2 Was the number of profiles in each conjoint task justified?
3.3 Was (should) an opt-out or a status-quo alternative (be) included?
4. Was the choice of experimental design justified and evaluated?
4.1 Was the choice of experimental design justified? Were alternative experimental designs considered?
4.2 Were the properties of the experimental design evaluated?
4.3 Was the number of conjoint tasks included in the data-collection instrument appropriate?
5. Were preferences elicited appropriately, given the research question?
5.1 Was there sufficient motivation and explanation of conjoint tasks?
5.2 Was an appropriate elicitation format (that is, rating, ranking, or choice) used? Did (should) the elicitation format allow for indifference?
5.3 In addition to preference elicitation, did the conjoint tasks include other qualifying questions (for example, strength of preference, confidence in response, and other methods)?
6. Was the data collection instrument designed appropriately?
6.1 Was appropriate respondent information collected (such as sociodemographic, attitudinal, health history or status, and treatment experience)?
6.2 Were the attributes and levels defined, and was any contextual information provided?
6.3 Was the level of burden of the data-collection instrument appropriate? Were respondents encouraged and motivated?
7. Was the data-collection plan appropriate?
7.1 Was the sampling strategy justified (for example, sample size, stratification, and recruitment)?
7.2 Was the mode of administration justified and appropriate (for example, face-to-face, pen-and-paper, web-based)?
7.3 Were ethical considerations addressed (for example, recruitment, information and/or consent, compensation)?
8. Were statistical analyses and model estimations appropriate?
8.1 Were respondent characteristics examined and tested?
8.2 Was the quality of the responses examined (for example, rationality, validity, reliability)?
8.3 Was model estimation conducted appropriately? Were issues of clustering and subgroups handled appropriately?
9. Were the results and conclusions valid?
9.1 Did study results reflect testable hypotheses and account for statistical uncertainty?
9.2 Were study conclusions supported by the evidence and compared with existing findings in the literature?
9.3 Were study limitations and generalizability adequately discussed?
10. Was the study presentation clear, concise, and complete?
10.1 Was study importance and research context adequately motivated?
10.2 Were the study data-collection instrument and methods described?
10.3 Were the study implications clearly stated and understandable to a wide audience?

8.18 Appendix 18 - Design Simulations





8.19 Appendix 19 - Percentage of Respondents by EQ-5D-5L dimension

Dimension	Level	Description	All N=1640 %	Normal weight N=630 %	Over weight N=552 %	Obese N=458 %
Mobility	1	I have no problems in walking about	70.7	83.3	70.3	53.9
	2	I have slight problems in walking about	17.5	11.1	17.9	25.8
	3	I have moderate problems in walking about	7.7	3.5	7.4	13.8
	4	I have severe problems in walking about	3.6	1.8	3.8	5.9
	5	I am unable to walk about	0.5	0.3	0.5	0.7
Self-care	1	I have no problems washing or dressing myself	87.5	92.2	87.5	81.0
	2	I have slight problems washing or dressing myself	7.5	4.4	5.6	14.0
	3	I have moderate problems washing or dressing myself	3.8	2.7	5.1	3.7
	4	I have severe problems washing or dressing myself	0.6	0.3	1.3	0.2
	5	I am unable to wash or dress myself	0.6	0.3	0.5	1.1
Usual activities	1	I have no problems doing my usual activities	70.6	79.7	71.2	57.4
	2	I have slight problems doing my usual activities	18.4	13.2	17.9	26.2
	3	I have moderate problems doing my usual activities	7.1	4.3	7.1	10.9
	4	I have severe problems doing my usual activities	3.0	2.1	3.3	3.9
	5	I am unable to do my usual activities	0.9	0.8	0.5	1.5
Pain / discomfort	1	I have no pain or discomfort	43.2	55.2	40.4	29.9
	2	I have slight pain or discomfort	34.4	30.2	37.7	36.2
	3	I have moderate pain or discomfort	15.3	10.6	14.0	23.4
	4	I have severe pain or discomfort	5.7	3.2	6.2	8.5
	5	I have extreme pain or discomfort	1.5	0.8	1.8	2.0
Depression / anxiety	1	I am not anxious or depressed	51.5	55.2	53.8	43.7
	2	I am slightly anxious or depressed	27.1	27.8	26.5	26.9
	3	I am moderately anxious or depressed	14.0	12.4	12.9	17.7
	4	I am severely anxious or depressed	4.2	2.7	3.8	6.6
	5	I am extremely anxious or depressed	3.2	1.9	3.1	5.2

8.20 Appendix 20 - Latent class membership demographics

		Class 1		Class 2		Class 3	
		N	%	N	%	N	%
	Female	2,160	39.2%	3,168	53.8%	7,184	48.0%
	Male	3,344	60.8%	2,720	46.2%	7,696	51.4%
Gender	Other	0	0.0%	0	0.0%	96	0.6%
	18-24	16	0.3%	400	6.8%	2,352	15.7%
	25-34	816	14.8%	928	15.8%	3,808	25.4%
	35-44	1,152	20.9%	1,072	18.2%	2,320	15.5%
	45-54	864	15.7%	912	15.5%	2,144	14.3%
	55-64	1,440	26.2%	1,232	20.9%	2,096	14.0%
	65-74	912	16.6%	992	16.8%	1,632	10.9%
Age	75+	304	5.5%	352	6.0%	624	4.2%
	Single, never married	1,216	22.1%	1,136	19.3%	4,176	27.9%
	Married	2,736	49.7%	3,440	58.4%	6,544	43.7%
	Living with a partner	464	8.4%	576	9.8%	2,640	17.6%
	Divorced	688	12.5%	576	9.8%	688	4.6%
	Separated	272	4.9%	64	1.1%	464	3.1%
	Widowed	112	2.0%	80	1.4%	304	2.0%
Marital status	Prefer not to say	16	0.3%	16	0.3%	160	1.1%
	Negative or zero income	0	0.0%	48	0.8%	272	1.8%
	$1 - $19,999	368	6.7%	304	5.2%	1,232	8.2%
	$20,000 - $49,999	1,760	32.0%	1,328	22.6%	3,056	20.4%
	$50,000 - $79,999	1,008	18.3%	944	16.0%	2,864	19.1%
	$80,000 - $109,999	816	14.8%	880	14.9%	2,480	16.6%
	$110,000 - $149,999	608	11.0%	672	11.4%	1,760	11.8%
	$150,000 - $199,999	240	4.4%	448	7.6%	752	5.0%
	$200,000 +	128	2.3%	304	5.2%	592	4.0%
	Don't know	160	2.9%	224	3.8%	432	2.9%
Income	Prefer not to say	416	7.6%	736	12.5%	1,536	10.3%

	Full time paid work	1,344	24.4%	1,456	24.4%	5,632	37.6%
	Part time paid work	1,040	18.9%	1,024	18.9%	2,160	14.4%
	Self-employed	464	8.4%	480	8.4%	1,104	7.4%
	Retired	1,472	26.7%	1,632	26.7%	2,048	13.7%
	Disabled/sick	160	2.9%	112	2.9%	528	3.5%
	Unpaid work	32	0.6%	16	0.6%	176	1.2%
	Studying	144	2.6%	304	2.6%	880	5.9%
	Unpaid housework	496	9.0%	464	9.0%	1,328	8.9%
	Unemployed	272	4.9%	320	4.9%	960	6.4%
Employment	Other (please specify)	80	1.5%	80	1.5%	160	1.1%
	Excellent	208	3.8%	416	7.1%	1,536	10.3%
	Very good	1,536	27.9%	2,128	36.1%	4,480	29.9%
	Good	1,920	34.9%	2,304	39.1%	5,440	36.3%
	Fair	1,440	26.2%	816	13.9%	2,544	17.0%
Health	Poor	400	7.3%	224	3.8%	976	6.5%
	Normal weight	1,792	32.6%	2,672	45.4%	5,648	37.7%
	Overweight	2,208	40.1%	2,064	35.1%	4,640	31.0%
BMI group	Obese	1,504	27.3%	1,152	19.6%	4,688	31.3%

8.21 Appendix 21 - Time preferences literature search

Database: Embase <1974 to 2017 January 31>, Ovid MEDLINE(R) Epub Ahead of Print, In-Process & Other Non-Indexed Citations, Ovid MEDLINE(R) Daily and Ovid MEDLINE(R) <1946 to Present>
Search Strategy:
----
1 ("time-preference*" or "hyperbolic discounting").ti,ab. (748)
2 *obesity/ or *overweight/ or (obesity or overweight or obese).ti,ab. (632774)
3 1 and 2 (24)
4 remove duplicates from 3 (14)
5 (editorial or erratum or letter or note or comment or commentary or conference abstract).pt. (6329869)
6 4 not 5 (11)

8.22 Appendix 22 - Time preference questions

Section 6

The final section will ask you 4 questions about your time preferences around rewards, penalties and health procedures.

The questions will ask you to choose between **two scenarios** with multiple **options that vary** the reward amounts, fees, costs or waiting times.

Question 1

Imagine you could choose between receiving **$500 now**, or **another amount 1 year** from now.

A) Please indicate which option you would choose:

- Receive $500 now
- Receive $510 in one year from now

Question 2

Imagine that you have been caught speeding by the police. You can either pay the **$200 speeding fine immediately**, or pay a **different amount in 6 months** from now.

A) Please indicate which alternative you would choose:

- Pay the $200 fine now
- Pay $400, 6 months from now

Question 3

Imagine you have pain and discomfort in your knee that limits your walking. Your doctor thinks that you need an operation on your knee to reduce the pain and help with your mobility.

The operation is not urgent and you have two options in terms of cost and waiting times:

- Option 1: the operation will **cost $500**, but you will need to **wait 12 months** for treatment.
- Option 2: the operation will **cost $2000**, but the **waiting time is shorter**.

A) Please indicate which option you would choose:

- Wait 12 months for the operation and pay $500
- Wait 10 months for the operation and pay $2000

Question 4

Imagine that you are overweight. To help you lose weight, the Government is willing to provide a **$300 incentive** to encourage you to **enroll in a free weight loss program**. This incentive is paid to you once you enroll in the program, and is not conditional on you losing weight.

Alternatively, the Government is offering **another scheme that pays a higher cash incentive,** but the payment is only available **if you lose an agreed amount of weight** (e.g. 5 kilograms).

Which option would you choose?

- Option 1: the **guaranteed $300 cash incentive now**, or
- Option 2: the **higher amount 6 months from now**, which is conditional on you losing weight?

A) Please indicate which incentive you would choose:

○ Receive $300 now
○ Receive $300 6 months from now, if you lose 5 kgs.

8.23 Appendix 23 - Feedback question and comments

Responses from all respondents who completed the feedback questions were included in the summary statistics. Overall, the majority of respondents (72.3%) indicated that they would prefer a combination of diet and exercise if they wanted to lose weight. The feedback about the difficulty of the survey was overwhelmingly positive. Over 80% of respondents found the survey either extremely easy or easy. Furthermore, the open text box resulted in many positivity messages about the survey. A subset of the comments can be found in below.

Feedback summary statistics

Feedback questions	n	%
1) If you wanted to lose weight, what type of program would you prefer?		
Diet only	215	13.4%
Exercise only	208	13.0%
Diet and exercise	1,156	72.3%
Other (please comment)	21	1.3%
Other		
Diet and light exercise		
Detox programs		
Life style change		
Remove all packaged food from supermarket		
Diet, exercise and counselling		
Better food choices		
Tailored diet and exercise		
Weight loss surgery		
Will power		
2) Please rate how easy or difficult the survey was to understand?		
Extremely easy	653	40.8%
Easy	671	41.9%
Neither easy nor difficult	232	14.5%
Difficult	35	2.2%
Extremely difficult	9	0.6%

Feedback from respondents

Comments
Love these surveys. Very interesting and fun to do
Fascinating - it made me think about gratification and rewards.
no great survey , keep them coming
Interesting
A very comprehensive survey
Everything here is too good! This is very easy survey ,I really enjoyed
This is a very interesting survey.
unique and very interesting!
Quite interesting
Interesting survey
Yes a sugar tax is a must!!! I liked this survey it was extremely relevant to me. However I don't agree at all with the government paying me nor anybody to lose weight. There has to be another non-cash incentive.
I thought it was a sensible survey
make it happen
Interesting survey

Interesting, but in these surveys no one is addressing people's perceptions of the food they eat, the food industry, and what their knowledge is of nutrition and the erroneous message given that fat is bad for people, when in fact, more healthy fats but less carbs can greatly contribute to weight loss without people going hungry. Exercise of its own will not aid much in permanent weight loss, nor taking in less calories, whereas a ketogenic diet can AND improve other health factors.
I am unable to do physical exercise as it is too painful and it is not due to weight. Diets cost too much and don't work. I can't afford all the diet stuff. It is up to the person to loose weight not for the government to tell people what they can and can't eat. We are not children.
Loved this survey
Great survey.. Thanks heaps..
This survey is really interesting.Thank you!
Survey was long.
Interesting. Thank you
It was good -I think my current living arrangements/distance from town influence my decisions.
Easy to understand
I wait for my weight to be wearable...its my choice.
Great survey
I enjoyed the scenarios. Was a good survey
5star survey
Make alot effort to loose weight
very interesting survey
no it was a good survey
its really interesting to do a survey like this
If only the presented scenarios were possible. In addition to financial insentives. I belive there should be an annual cash reward for maintaining healthy weight. This would take massive pressure off the health system and be more financialy viable in the long run.
Very interesting
an excellent survey with pertinent questions
a lot of us want to lose weight, but when pain is a major factor its too hard
very interesting
none. The Government should consider free gym memberships via scrip from Doctor if it is a health issue.
very interesting & differenct survey good onya
good interesting survey
Well structured survey
It seems to be a mistake in the very question. It asks if I would prefer to be paid$300 immediately with no result necessary or a higher amount at completion of program and having achieved a particular goal. However both answers state $300 as the reward. Small mistake I know, but hey, you asked. ðŸ˜Ž
it's all about lifestyle choices-everyone makes their own
had cancer earlier this year so am more interested in re-gaining weight no loosing it
It was fun and interesting.
I enjoyed this survey and really hope the government will help with this issue and bring light that there isnt any wrong with them personally but it is better for help to get fit
I am 73 years old and fairly fit but want to lose 10 KG and some of my gut.
any program that is the cheaper option i would select,but i would do the training myself an not pay for a gym.
I am currently losing weight, so this survey was interesting to me.
Easy Some things in this need to be put into place. Make weight loss a way of life
Good survey, interesting topic and very easy to answer (read very user friendly)
No it was clear
Somewhat bizarre alternatives offered more designed to explore my psychology than based on reality.
It was interesting. I really enjoyed doing it.
I worry about the healt effect of rewarding people to lose weight. I feel it could encourage disordered eating or exercise.
Any programme's I participated in I would only do if I knew I had continual support from a trusted 3rd party who is willing and able to attend with me otherwise I know I would not see it through
These metrics don't allow for people who have conditions like TMAU which Aussie Dr's don't recognise, unlike the UK it isn't on medicare despite being debilitating and diet not helping for many women. Permanent

exhaustion, skin lesions, stench, can't work, in pain constantly, can't sleep or sleep for 16 hours straight and nobody takes it seriously. There are a LOT of people with this condition stuck indoors doing surveys- results will be skewed.
interesting and different
If you are a heartburn, you can not spot a slice to lose weight, because you can not withstand your heart, so the diet is the aid to him.
Was satisfying
have been battling weight issues for years under a dietician with very little success due to arthritic knees which do not help the exercise plan due to pain
Interesting options
Your questions on diet all focussed on reduced-calorie diets, which are the hardest to use effectively (since they cause hunger). Had you included questions on reduced-carbohydrate diets, the answers would have been rather different. Likewise your questions about exercise focussed on desire to lose weight, which is just plain silly (effective exercise programmes lead to weight gain, not loss). If you want to bring exercise into the mix, you should ask about desire to reduce circumference (rather than weight). Sound like splitting hairs? It isn't: muscle is denser than fat -- the maths are fairly straightforward from there.
Very good survey and happy to do this type again....Thanks
good topic affecting lots of Aussies
Interesting topic
No - enjoyed it as it was quite different from other surveys
Nice survey. I found it enjoyable and useful.
was interesting to complete
good luck getting people to lose weight!
interesting. However, my experience with people is that many slippery types are out there who would try and game a program like this, and rip taxpayers off. I also think it is an extension of the nanny state, and provides lightweight jobs in running and managing and monitoring such programs, to people who should try and get a real job.
When I regularly played sport, I did not need to lose weight but the pain I have is in my neck and refers down my shoulders to fingertips plus back. Some days I cannot lift my head from the pillow and need painkillers to move at all
I created my own diet without giving up any types of food-- day 1 miss breakfast just eat 1 piece of fruit,day 2 miss lunch, eat 1 piece of fruit, day 3 miss dinner eat 1 piece of fruit 4th day normal then repeat 1-3. when target weight achieved add back one meal ie breakfast on day one. check weight and continue accordingly--too easy
People like given cash incentives to lose weight but it should only be given if the person has lost a significant amount of weight. The other alternative is to give a cash incentive based on the amount of weight lost; ie the more weight lost, the higher the cash incentive.
thanks for the opportunity guys ...hope you can give more points for this....

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