Community Weight Loss Programmes - Applying Traditional and Behavioural-Economic Approaches to Help Understand When They Are Cost-Effective

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Intellectual Property and Publication Statements

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

Adult obesity remains a public health crisis with little sign of abating. Interventions to tackle obesity are many, and funding choices should be supported by evidence on value for money. A key issue with the economic assessment of weight-management programmes is that effectiveness should be extrapolated into the future, and therefore predictions should be made regarding long-term weight-change. However, as these weight-trajectories are often unknown, assumptions must be made within the model. In previous models, weight-trajectory assumptions are often basic and comprehensive sensitivity analysis of these weight-trajectories is rare.

This PhD aims to improve the best practice of cost-effectiveness modelling for weight management programmes and test various scenarios regarding weight-trajectories following these programmes. Economic and behavioural economic theories of weight-management were identified and used to build a framework to explain decision making regarding weight-management, and predict weight-change. A meta-regression model to predict weight-regain following weight-management programmes was then built. Following this, a longitudinal dataset of a sample of the UK population was analysed to predict a background weight trajectory.

The cost-effectiveness model used the Slimming World programme as a case-study, and combined the previous workstreams to inform weight-trajectories of the participants, parameters, and various sensitivity analysis, including scenarios used in economic evaluations from the literature. The research found that assumptions regarding weight-regain were the key driver of cost-effectiveness, and that assumptions used by previous economic models may have caused large inaccuracies in estimations of cost-effectiveness.

This PhD provides guidance to future projects estimating long-term cost-effectiveness of weight-management programmes. Policymakers will also gain an improved understanding of the potential weight-trajectories following weight-management programmes, and the impact than these long-term trajectories can have on the overall cost-effectiveness of the programme. This should lead to more accurate estimates of the value of interventions, and greater confidence in preventative healthcare spending decisions.

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Abbreviations

BMI: Body Mass Index

BOCF: Baseline Observation Carried Forward

BWM: Behavioural Weight-Management programme

CVD: Cardiovascular Disease

DALY: Disability-Adjusted Life-Year

ELSA: English Longitudinal Study of Aging

GDP: Gross Domestic Product

GLM: Generalised Linear Model

GP: General Practitioner

HSE: Health Survey for England

IMAGE: Individual Motivation And Group Experience

IMD: Index of Multiple Deprivation

LOCF: Last Observation Carried Forward

LSOA: Lower Super Output Area

MI: Myocardial Infarction

NHS: National Health Service

NICE: National Institute of Clinical Excellence

OLS: Ordinary Least Squares

PSA: Probabilistic Sensitivity Analysis

QALY: Quality-Adjusted Life-Year

RCT: Randomised Controlled Trial

SD: Standard Deviation

SSB: Sugar-Sweetened Beverage

SW: Slimming World

SWoR: Slimming World on Referral

T2D: Type II Diabetes

VIF: Variance Inflation Factor

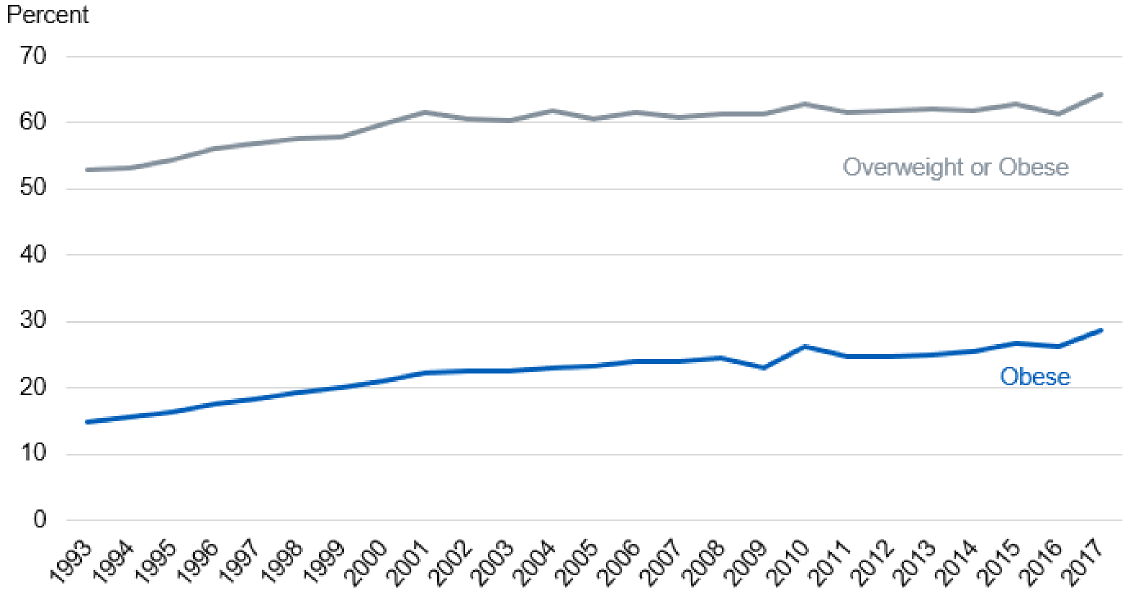
VLCD: Very-Low Calorie Diet

Chapter 1: The Obesity Problem in the United Kingdom

1.1 Introduction

Obesity is a growing public health challenge in the UK with 29% of adults being classified as obese in 2017 (NHS Digital, 2019). This is concerning due to this level being comfortably above the OECD average of 19.5% and gives the UK the 6th highest level of obesity amongst OECD countries (Devaux et al., 2017). The prevalence rate in England has trended upwards over time, almost doubling since 1993, where the obesity rate was close to 15%, shown in Figure 1. The OECD predicts a continuation of this growth, with the obesity rate in England expected to rise to 35% by the year 2030 (Devaux et al., 2017). As well as the increased prevalence of obesity rising, the combined rate of overweight and obesity has risen over the last two decades with close to two-thirds of the population of the UK currently being heavier than a healthy-weight (NHS Digital, 2019a). The rate of morbid obesity rose from 1% to 4% between 1993 and 2017 (NHS Digital, 2019a).

Figure 1: Adult Overweight and Obesity Prevalence Rates in England (NHS Digital, 2019a).



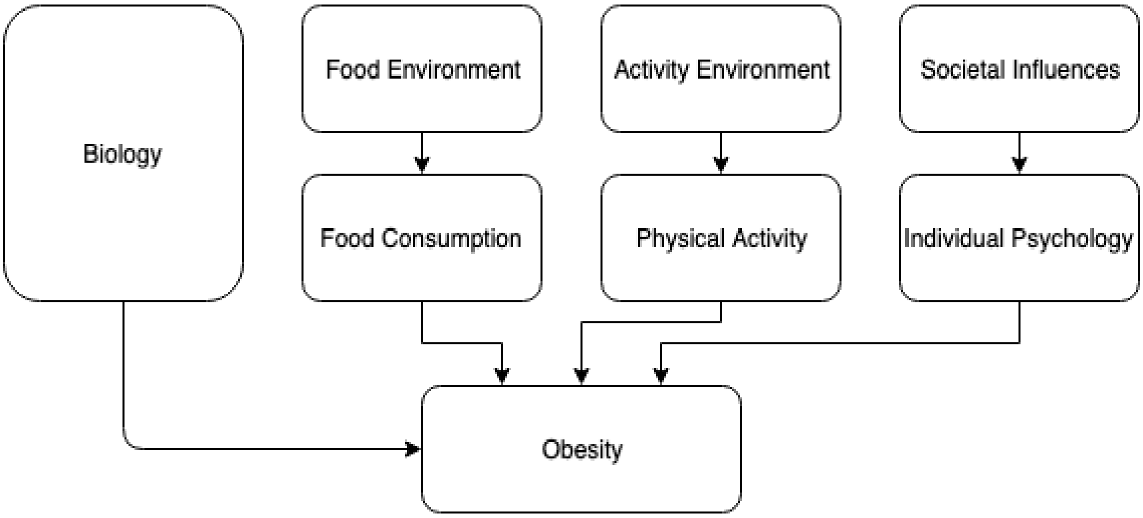
1.2 BMI as a Measure of Obesity

Obesity is defined using an individual's BMI, which is calculated by dividing weight in kilograms by height in metres squared. Individuals are defined as overweight if their BMI is above 25kg/m², whilst individuals with obesity are those with a BMI over 30kg/m² (WHO, 2016). There is a strong correlation between BMI and a number of diseases which shows that BMI is a good indicator of health risk (Department of Health, 2011).

1.3 Determinants of Obesity

One of the problems in slowing the increase of obesity, is that there are many complex behavioural and societal factors that have affected the increase in average population calorie intake, and the reduction in calorie expenditure (Butland et al., 2007; Chan and Woo, 2010). Because of this, there is no simple solution to resolve the obesity issue at a population level. The Foresight report (Butland et al., 2007) lists seven influencers of obesity at the individual level (Figure 2).

Figure 2: The Influencers of Obesity



The first factor affecting obesity is biology, which includes both the effect of genetics and the effects of sickness. Individuals have heterogeneous metabolic rates which are influenced by weight, age, and other biological factors (Johnstone et al., 2005). Generally, younger and heavier individuals have faster metabolisms than other individuals which means that individuals will maintain their weight at differing calorie intake and expenditure levels. As well as having heterogeneous metabolic rates, it is also the case that people have differing appetites, and so some will satisfy their hunger with a smaller amount of food, whilst some will require more to reach this satiety point (van der Klaauw and Farooqi, 2015).

Food consumption is the next factor involved in obesity prevalence. Because food consumption determines the total calorie intake for an individual, it is a large factor of whether an individual is in a calorie deficit or surplus, and therefore loses or gains weight. Therefore, individual choice regarding food consumption is a significant factor contributing towards obesity. Similarly, physical activity is a key determinant of calorie expenditure, as exercising requires energy. As well as this, more intense and prolonged exercise causing a larger calorie expenditure which can cause a larger calorie deficit and result in larger weight-loss.

If an individual desires a healthier diet, achieving this healthier diet may be unfeasible if the local environment does not accommodate this. For example, there may be few healthy food shops in the area, or the individual may be unable to afford a healthier diet. As well as this, the opportunity for activity in the individual's local environment can influence the level of physical activity undertaken. For example, are there sports clubs and gyms in the area that are affordable? Are there safe cycling routes? Is the area safe to exercise alone? If these requirements are not met, even if an individual wants to participate in physical activity, it may be inconvenient if the local environment presents limited opportunities to do so.

The final direct influencer of obesity is individual psychology, and the impact of decision making on weight management. Individuals can have heterogeneous psychological drives for particular foods and consumption patterns, or physical activity patterns, which can in turn affect bodyweight. Different individuals will also have heterogeneous reactions to external stimuli, with some being more tempted than others by advertising, smells and packaging (Ruhm, 2012).

Societal influence can influence individual psychology in regards to weight decisions. This may include the impact of the media in determining people’s ideal body weight, what children are taught in school, peer pressure to lose weight or eat calorie dense food and drink, and culture. Culture has an important influence on individual habits. For example, a typical night socialising for individuals may involve eating a calorie dense meal whilst drinking alcohol, which are viewed as empty calories. If an individual wants to lose weight, then they may have to forgo this social experience, or have a low-calorie meal and water, which may conflict with societal norms.

1.3.2 Causes of the Increase in Obesity

The economic focus on growth is one reason for the increase in the obesity rate globally. Increased economic growth and consumerism is causing an increase in demand for food, beverages and technology that reduces exertion of energy. These three factors all increase the average calorie surplus and therefore the obesity rate (Ananthapavan et al., 2014).

Cawley (2004) explains how the increase in obesity prevalence over the past couple of decades can be explained by technological change. Mass preparation of food has led to lower prices through increased supply, which has increased the amount of food that each individual can afford, and resulted in a larger quantity of food demanded (Lakdawalla and Phillipson, 2002; Lakdawalla and Phillipson, 2009). Technology has also reduced waiting times with the ability to quickly make meals in microwaves and purchase meals from the growing number of fast-food outlets.
Also, due to technological change, food variety has risen, which has led to an increase in snacking between meals (Cutler et al., 2003; Sorensen et al., 2003). Between 1978 and 1996 in the United States, Cutler et al. (2003) found that average calorie intake rose by 268 per day for men, and by 143 for women. In men, 90% of this calorie increase came from extra snacking, with snacking causing 112% of the calorie intake increase in women. This implies that the average calorie intake from meals has stayed fairly constant, and that women in 1996 were actually consuming less calories from meals than women in 1978.

Technological change has also caused work to be more sedentary. Many manual labour jobs are being automated and people are more and more often working from desks and burning very few calories. Phillipson and Posner (1999) state that due to technological change, people now have to pay for exercise in terms of both time and money rather than being paid to do physical activity when manual labour jobs were more common. Lakdawalla and

Phillipson (2007) found that men who spend 18 years working in the highest ranked “fitness demanding” labour jobs are on average 14% lighter than those in the lowest ranked. This is represented as a difference in BMI of 3.5kg/m^2. The changing role of women in society is also thought to be a contributor to the change in obesity prevalence rate. Anderson et al. (2003) found significant evidence of a causal effect of maternal employment on the probability of a child being overweight. This could be due to parents being less able to supervise eating and exercise. If one of the parents is working less it means that less of their time is expended on work, and there will be more time available to shop for food, cook meals, play with the child, and take them to play sports or participate in outdoor activities. It is possible that these habits developed by the child at an early age are taken forward into later life (Anderson et al., 2003). Leisure activities for children have also seen a large shift from hobbies that are active to hobbies that are more sedentary, such as video games and watching television (Vandewater et al., 2004).

Another factor in the rise in obesity has been the fall in the total number of smokers in the population (NHS Digital, 2019b). Courtemanche et al. (2016) estimated that quitting smoking leads to an average weight gain of 11-12 pounds, which was estimated to account for around 14% of the rise in obesity in the United States. Since 2010, the smoking rate amongst adults in the UK has fallen from 19.9% to 15.5%, so it is likely that the reduction in the number of smokers has contributed to the rise in the obesity rate in the UK also.

In a study by Lakdawalla and Phillipson (2002) using data from 1974-1996, the researchers attributed around 40% of weight growth to agricultural innovation lowering food prices and 60% to demand factors such as physical activity changes at home and at the workplace. Cawley (2015) in a review of economic research on obesity, concluded that there is no single main cause of the increase in obesity which makes providing population level interventions challenging for policymakers.

1.4 Health Effects of Obesity

The main concern with the increase in the obesity prevalence rate in the UK is that obesity increases the risk status for a number of diseases. Men with obesity are five times more likely to develop Type 2 diabetes than a male of healthy weight, three times more likely to develop colon cancer, and two and a half times as likely to have high blood pressure, which can cause stroke and heart disease (Department of Health, 2011). Obese women are almost 13 times more likely to have Type 2 diabetes, more than four times more likely to have high blood pressure, and more than three times as likely to suffer a heart attack than their healthy weight counterparts (Department of Health, 2011). Individuals with obesity also have a higher risk of other diseases, including angina, gall bladder disease, liver disease, ovarian cancer, and osteoarthritis (Department of Health, 2011). Research has shown a total of 18 comorbidities that have a statistically significant relationship to obesity (Guh et al., 2009). An estimated 7.1% of deaths in England and Wales in 2014 were attributed to overweight and obesity, with each individual losing an average of 12 years of life which equals a total of 430,029 life years (Tovey, 2017).

The Global BMI Mortality Collaboration (2016) found in a meta-analysis of 239 studies on obesity that identified the hazard ratio[1] of each BMI group compared with a healthy BMI of 18.5-<25.0kg/m^2. Before filtering the participants, the analysis found a reduced hazard ratio of 0.95 for those overweight (BMI of 25.0-<30.0kg/m^2) but an increase in each subsequent group with those severely obese (BMI of 40.0-<60.0kg/m^2) having a hazard ratio of 1.95. After filtering participants to those that had never smoked, had no known chronic disease at baseline and excluding the first 5 years of follow-up, the researchers found those that were overweight had an increased hazard ratio of 1.11 and this rose up to those that were severely obese having a hazard ratio of 2.71.

A collaborative analysis of 57 studies on the relationship between BMI and mortality found a strong positive correlation (Prospective Studies Collaboration, 2009). The analysis revealed each 5kg/m^2 higher BMI was correlated with around a 30% higher rate of mortality. At a BMI of between 30 and 35kg/m^2,

[1] Hazard ratio signals the ratio of deaths in the group compared to the baseline group (normal weight)

median survival fell by 2-4 years whilst those with a BMI of between 40 and 45kg/m^2 had their median survival reduced by 8-10 years. In 2015, being either overweight or obese caused 7.1% of all deaths globally (Mokdad, 2017). As well as these negative effects on life-expectancy, obesity also reduces physical functioning with individuals with obesity having a lower functional capacity than those of a healthy weight (Pataky et al., 2014).

1.5 Costs of Obesity

In addition to the negative public health effects that come with having a high obesity rate, there are also costs that come with treating diseases, costs to society and businesses, and costs to the individuals themselves. Globally, obesity is estimated to cost society $2 trillion each year (McKinsey & Company, 2014). In a UK context, obesity has the second greatest human generated impact on the UK (after smoking) – one that costs $73 billion each year, equivalent to 3% of GDP (McKinsey & Company, 2015).

1.5.1 Public Health Costs

In a systematic review of the economic effects of obesity, Yusefzadeh et al. (2019) found that around 10% of health care costs are directly and indirectly attributable to adult obesity. This equates to an obese individual having 32% higher health care costs than a person of normal weight on average.

The UK government reported that an estimated £6.1bn was spent in 2014 to 2015 on medical costs associated with overweight and obesity, and is expected to reach £9.7bn by 2050 (Public Health England, 2017a). This is a substantial burden for the NHS budget, and one that is growing. A systematic review that included 23 studies on the economic burden of obesity concluded that there is an urgent need for public health measures to reduce the obesity prevalence rate (Tremmel et al., 2017).

As the NHS has limited resources, it cannot afford to treat every health problem across the population. NICE must therefore prioritise which treatments to fund based on the cost-effectiveness of each treatment – weighing up the effectiveness of the treatment in terms of improvements to quality of life, gains to life years, against the cost of the treatment (Weinstein, 2009). With diseases relating to obesity taking up an increasing percentage of the NHS budget, this results in resources being taken away from other diseases and redistributed towards co-morbidities of obesity, further damaging the population's health.

1.5.2 Societal Costs

As well as direct healthcare costs there are also wider costs to society that must be considered. As obesity causes health problems there is productivity loss due to illness as well as underachievement in education, lower engagement in society and discrimination in the workplace (Goettler et al., 2017). Butland et al. (2007) estimates that wider societal costs of overweight and obesity are around 7 times that of direct healthcare costs in the UK which represents a substantial proportion of GDP. By reducing the prevalence of obesity, the UK stands not only to gain from the reduced healthcare burden, but also from increased productivity and output. Public Health England (2017b) estimated that the cost to wider society is £27 bn. This is expected to reach £49.9bn by 2050.

1.5.3 Individual Costs

Individuals with obesity face a number of negative effects associated with their weight, with the main problem being poor health and co-morbidities. As well as health problems, individuals with obesity also face wage penalties in the workplace (Cawley, 2004). This could be caused by lower productivity due more sick days or discrimination – both in applying for jobs and when being considered for promotions. Discrimination from society due to weight can also lead to mental health problems and increase the likelihood of further weight gain (Sutin and Terracciano, 2013).

1.6 The Problem

To tackle the obesity problem, companies in the private sector, such as Slimming World and Weight Watchers, have developed community weight-loss programmes which aim to help customers adjust their lifestyles and weight-management behaviours (Slimming World, no date a; The New Weight Watchers, no date). These programmes have been successful in helping customers lose weight whilst they attend classes that promote healthy lifestyles and weight-management behaviour. A recent systematic review of over 1 million behavioural weight-loss programme participants showed a mean weight-loss of 3.9kg at 3 months (Stubbs et al., 2015). However, once participants leave these programmes, little is known about whether individuals maintain their weight-loss, continue to lose weight, or regain weight.

One strategy undertaken by NICE to combat the rising obesity rate and reduced the rates of diseases associated with obesity is referral of individuals with obesity to commercial weight-management programmes (NICE, 2014). These programmes aim to help participants adjust their lifestyles in order to improve weight-management behaviour. To accurately assess whether these programmes offer long-term value for money, the effectiveness and associated costs should be measured over the course of a lifetime. To gain an understanding of the potential outcomes and costs of referring individuals to these weight-management programmes, the long-term cost-effectiveness of referral should be assessed via modelling methods. The key issue with the assessment of weight-management programmes however, is that weight-trajectories after people leave the programme are unknown, and therefore long-term costs and effects associated with weight-change are unknown. Therefore, assumptions must be made regarding the long-term weight-change of participants. Currently in the literature, assumptions are often basic in regards to weight-trajectories, and comprehensive sensitivity analysis of these weight-trajectories is rare.

1.7 Aims and Objectives

This PhD will aim to improve the best practice of cost-effectiveness modelling for weight-management programmes, and test various scenarios regarding weight-trajectories following these programmes. To achieve this aim, the following questions will be answered.

1. Which economic and behavioural economic theories explain how individuals behave in regards to weight management?

2. Are the hypothesis made by the theoretical framework reflected in real world data?

3. How have economic evaluations of weight management programmes been modelled in the past?

4. What weight-trajectories can be expected following the completion of weight-management programmes?

5. What is the impact on cost-effectiveness of adjusting assumptions regarding long-term weight-trajectories?

The first stage of the PhD (Q1) is to identify how economic and behavioural economic theories explain weight management behaviour. A systematic review of current literature is undertaken to find theories that can be used to explain weight management decision making. The theories identified are then be used to form a theoretical framework of individual weight management behaviour.

The second phase (Q2) uses a case study, the Slimming World weight management programme, to provide evidence for this theoretical framework regarding the influencers of weight-change, using a large dataset. The framework is then be used to make predictions about how individuals, both those who remain in the programme, and those who leave, will fare with weight-change in the two-year intervention period.

The third phase (Q3) examines how the longer term cost-effectiveness of weight management programmes has been modelled. A review of the literature is undertaken, with focus on the assumptions made and the methods employed. Information found from this review is used to inform the modification of a cost-effectiveness model.

The fourth phase (Q4) reviews the long-term follow up of behavioural weight-management in the literature to gain an understanding of the weight-trajectories that can be expected following the completion of a weight-management programme. This information is then used to form more general predictions of weight-trajectories after individuals leave weight-management programmes.

The penultimate phase (Q5) draws on the preceding phases to develop a cost-effectiveness model, and model cost-effectiveness for the case study - the Slimming World programme. The predictions of weight-change within the Slimming World programme and predictions of weight-trajectories following weight-management programmes inform weight-change in the model, whilst the review of modelling literature informs the modifications to more general assumptions, and assumptions regarding the control group. Finally (Q6), sensitivity analyses are performed on the uncertain parameters within the model, including weight-change each year, to assess the impact of adjusting parameters on cost-effectiveness.

The thesis therefore aims to provide information about the factors which determine the success of lifestyle weight-management programmes. By doing this, service providers will be able to improve their programmes to take into account individual characteristics, demographics and habits. Policymakers will also gain an improved understanding of weight-trajectories following weight-management programmes, and the impact than these long-term trajectories can have on the overall cost-effectiveness of the programme. The cost-effectiveness model will also provide guidance on future projects estimating long-term cost-effectiveness of other public health programmes. This should therefore lead to more accurate estimates of the value of interventions, and greater confidence in preventative healthcare spending decisions.

Chapter 2: Can Economic and Behavioural Economic Theories help to Explain Weight Management Behaviour? A Systematic Review

2.1 Background

When estimating the value of weight management programmes, it is important to consider long-term effects. In order to estimate long-term weight trajectories it is useful to consider economic and behavioural economic theories of weight management so predictions can be made regarding outcomes according to individuals' characteristics.

Economic theory states that individuals that play a part in the economy have the goal of maximising their own utility (Aleskerov et al., 2007). Neo-classical theory makes the assumption that individuals have perfect information and are rational, and so can exactly assess how much expected utility they will receive from all options they have available to them, once probabilities and payoffs have been taken into account (Weintraub, 1993). However, behavioural economics recognises that some of the assumptions made by economic theory can limit the validity of predictions. Behavioural economic theory therefore loosens some of these assumptions in order to capture the heterogeneity, and sometimes lack of rationality, in the behaviour and decision making of individuals (Just, 2014).

This review aims to identify economic and behavioural economic theories that explain individual's decisions regarding weight change, what motivates them to make these decisions, and irrational behaviours that can lead to sub-optimal body weight outcomes. This will be done to better understand the decision-making of individuals who are attempting to lose weight, and those who are attempting to maintain weight loss.

The methods section is presented next including a description of the search strategy, the inclusion and exclusion criteria and the data extraction. Following this, the basic economic framework is presented as an introduction to the economic and behavioural economic theories in the review. Three themes of weight management behaviour that came forth during the data extraction are discussed. These three themes are rational choice, where it assumed people act with perfect rationality, time-preference, where the timing of returns affects decision making, and habits and self-control, which affect how individuals behave. In each of these sections the theories identified are discussed alongside any empirical evidence identified. The discussion section then summarises the main findings from the review.

2.2 Methods

A preliminary search of Medline was performed using key terms such as ‘economic theory’ alongside terms including ‘weight maintenance’ and ‘weight management’ to identify the most common keywords in the literature that could be used to perform the main search. The books “Health Economics”, “Methods for the Economic Evaluation of Health Care Programmes” and “Behavioral Economic and Public Health” were consulted to find theory names that could be used as search terms to identify papers (Pauly et al., 2012; Drummond et al., 2005; Roberto and Kawachi, 2015). From here a comprehensive list of search term combinations was compiled in Table 1, where terms in each column were combined by “OR” and the four columns are combined by “AND”. Therefore, papers identified must have had at least one keyword from each column. Two additional smaller scale searches were also performed. The first search combined columns 1+2+3 using “AND”. The second combined columns 1+4, using “AND” also. This search was run in Medline, Embase, PsychINFO, The Cochrane Library, Web of Science, Econlit and CINAHL. All searches were run between 3rd May 2016 and 24th May 2016.

Table 1: Search Terms used in Theory Identification

1	2	3	4
“Overweight ”	“Economic* “	“Model “	“Willpower “
“Obes* “	“Behavioural Economic* “	“Theory “	“Rational* “
“Weight trajectory* “	“Behavioral Economic* “	“Framework “	“Bias* “
“Weight Loss “		“Approach “	“Habit* “
“Weight Maint* “		“Principle “	“Self-Control “
“Weight Management “		“Hypothesis “	“Self-Regulation “
			“Behav* “
			“Time-Preference “
			“Present Bias* “
			“Hyperbolic “
			“Discount* “
			“Peer Effect* “

			“Information Deficit “
			“Prospect Theory “
			“Rational Choice “
			“Ego Depletion “
			“Imperfect information “
			“Heuristics “
			“Framing “
			“Incentiv* “
			“Consumer Choice “
			“Bounded Rationality “
			“Dual System Theory “
			“Dual Decision Theory “
			“Grossman “
			“Salience “
			“Utility Maximi* “
			“Rational Addiction “
			“Primrose Path “
			“Myopic Addiction “
			“Status Quo Bias “
			“Habitual Behav* “

2.2.1 Inclusion/Exclusion Criteria

Inclusion and Exclusion criteria were set to ensure that only papers relevant to the research question were included in the review. The criteria that papers must meet to be included are listed below.

- Only individuals over the age of 18 as generally weight management programmes are aimed at those over the age of 18.

- The studies discuss either an economic or a behavioural economic theory focused on explaining individual weight change, as discussing these theories was the aim of the review.

- Studies focus on individual decision-making rather than population level causes of the rise in the obesity prevalence rate, as the aim of the review is to make predictions about individuals after a weight management programme.

- Only papers that involve lifestyle interventions, due to the fact that these are the interventions that focus on behavioural change.

- Papers may involve individuals with co-morbidities such as diabetes, but are focused on weight rather than the co-morbidity itself, as the focus is on reviewing theories relating to weight management, not the co-morbidities related to weight.

- The studies involved are all English language papers for practical reasons, but there was no constraint on the country of origin.

2.2.2 Data Extraction and Synthesis

Once the search was run and duplicates had been removed, titles and abstracts were screened. Ten percent of the papers were selected at random to be checked by a second reviewer against the inclusion/exclusion criteria, followed by discussion and agreement over any discrepancies in choice. Following this, the approved papers were reviewed in order to decide whether they should be included in the review. All the papers that were approved to be used in the systematic review were agreed upon by the second reviewer.

Data extraction was performed using a bespoke data extraction form, shown in Appendix 1, created with the aim of collecting the most relevant data from each of the selected studies. The form included the author and date of the paper, the themes that the paper was grouped into, a short summary of the theory, and whether any empirical evidence was included in the paper.

The theories extracted were grouped into themes depending on the focus, assumptions and predictions of the theory. A narrative synthesis was undertaken to discuss the roles of the theories in explaining individual weight management. Theories that are intuitive and proven in empirical tests may inform how individuals with heterogeneous characteristics behave in regards to weight management, which can help shape predictions regarding who should be most successful at managing their bodyweight.

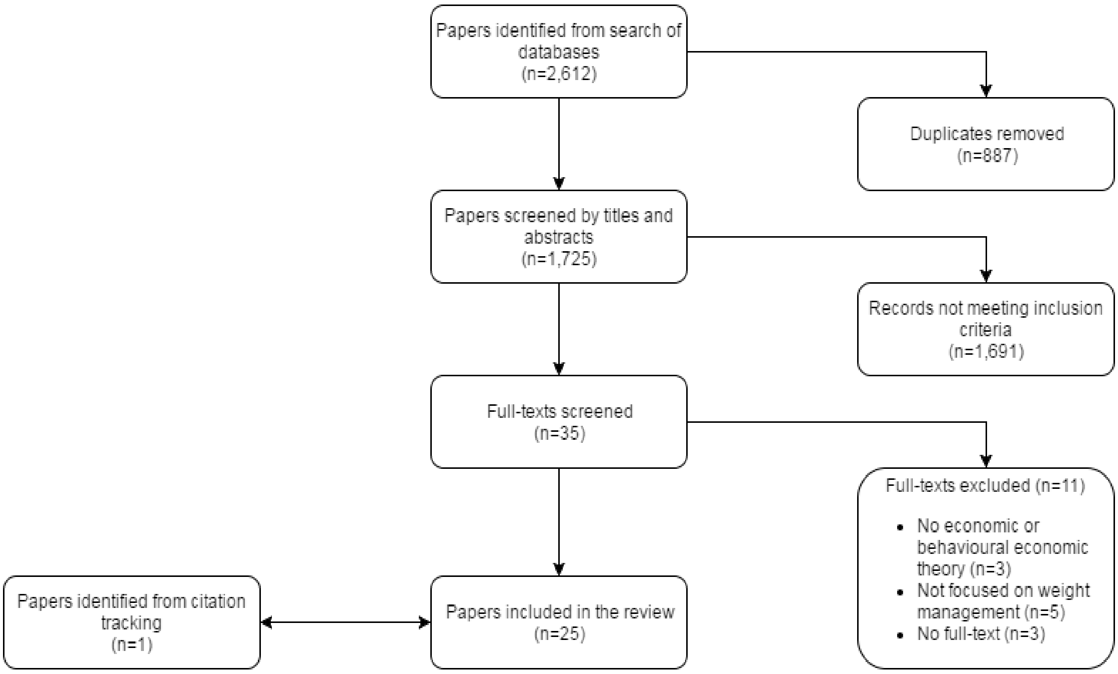
2.2.3 Citation Tracking

Whilst some of the papers in in the review included empirical testing of the theory described, others did not. In order to enhance the comprehensiveness of the review, each paper's citations were tracked using google scholar in order to find empirical tests of the theory that may have been published. To narrow the search, the citation search only identified citations if they had either of the terms "obesity" or "weight" in the title. Papers that had over 100 identified citations were limited to citations published from 2012 onwards for practical reasons. Titles and abstracts of these citations were then read to identify any empirical tests of the theory of interest, or whether any new or adapted theories were described that met the initial inclusion criteria but were not included in the previous searches.

2.2.4 Results

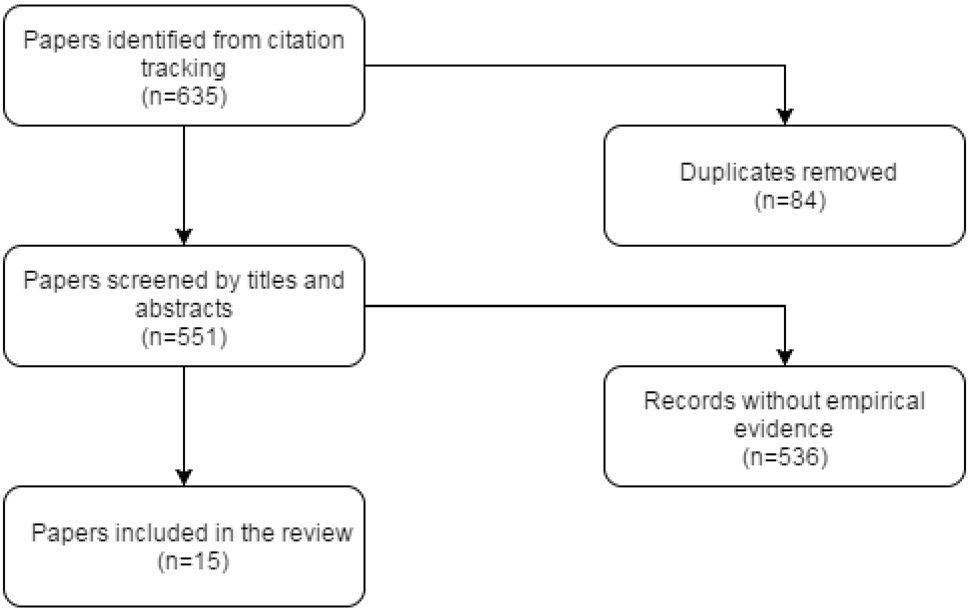
From the search of the ten databases 2,612 papers were found. A total of 887 duplicates were removed, initially using the Endnote duplicate removal tool followed by a manual check to leave 1,725 unique papers. From here, papers were screened by their title and abstract against the inclusion and exclusion criteria, which led to the removal of 1,691 of these papers. The 35 studies remaining were then read in full against the inclusion and exclusion criteria. Eleven of the full text papers were dropped, which left 24 papers that matched all of the inclusion criteria and are included in this review. One further paper was identified through citation tracking of the original 24 papers, resulting in a total of 25 papers included in the review. Figure 3 shows a flowchart of database searches. A total of 15 theories were discussed: 6 in the rational choice theme, 3 in the time-preference theme, and a further 6 in the habits and self-control theme.

Figure 3: PRISMA Flowchart



The next section of the results section discusses the citation tracking search, which had the purpose of finding empirical papers which provided evidence of the theories included in the review. The citation tracking search identified a total of 635 papers, which was reduced to 551 after de-duplication by title and author. The flowchart of the identification of papers is shown in Figure 4. Fifteen of the papers were included in the final review, and are summarised in Appendix 2. These papers were not included in the initial review as they were focussed on empirical testing rather than theory, and so did not meet inclusion criteria. The next section will discuss these theories that were identified and the empirical evidence found alongside them.

Figure 4: Flowchart of the Empirical Evidence Identification Process



2.3 How do current economics and behavioural economic theories explain weight management?

The papers included in the review identified several economic and behavioural economic theories that provide explanations of how individuals make their decisions relating to weight management, and the factors that influence these decisions. These have been grouped into themes, according to the underlying premise, assumptions and predictions that they make. The three general themes are 1) rational choice, 2) time-preference, and 3) habits and self-control. Within these three themes, there exists variations in the explanations of the way individuals make their decisions and what influences their decisions regarding weight management behaviour, but they share much common ground.

2.3.1 Theme 1: Rational Choice

2.3.1.1 Utility maximising weight is higher than ideal weight

Traditional economic theory sets the groundwork as to why individuals' main priority may not be their weight management. Rational choice theory is set in the neo-classical economic framework which states that individuals are rational and aim to maximise utility. Within this framework, as an individual's body weight is not their only source of utility and individuals must maximise utility subject to constraint and competing preferences, an individual may choose to sacrifice their ideal weight for utility in other areas. This can result in equilibrium weight being at a weight higher than the individual's ideal weight. Therefore, it is a rational decision to be overweight (Richards and Hamilton, 2012). For example, different individuals will place differing values on being at their ideal weight, have different eating habits, gain different levels of enjoyment, or displeasure, from cooking and exercising, and have different access to foods and exercise methods (Grunert et al., 2012). Before making a decision, individuals are assumed to weigh up the potential costs and benefits of all their actions and choose the combination of options that provide the highest expected utility (Finkelstein et al., 2004).

If the total benefits of the consumption of a certain food (the pleasure from eating, the satisfaction of stopping hunger, and the requirement of nutrition for survival) outweigh the costs (price, time spent preparing the food, and future weight and health effects) then the individual will consume the food regardless of whether it will cause weight gain. Finkelstein et al. (2004) suggests that in the current environment, it is likely that there are several conditions that exist that lead individuals to sub-optimal food decisions, and result in over-consumption from both the perspective of the individual and society. Sun (2016) performed a study to find the optimal weight using mathematics and qualitative theory. The study found that the optimal weight for both males and females was greater than the health maximising weight.

Dual decision theory attempts to explain the interaction between the rational decision making process and impulsive decision making (Ruhm, 2012). The deliberative system follows the traditional economic framework in which individuals behave under a number of assumptions in order to maximise utility, whilst the affective system is more closely related to habits and self-control, and will be discussed later. The maximisation problem for the deliberative system is shown in Equation 1, where U is utility, W is weight, f is food consumption, c is other consumption, p is price and I is income. Here, individuals maximise their utility through their weight (which is a function of food consumption), food consumption and other consumption subject to their income constraint.

Equation 1

$$\mathrm{Max}_{f,c}\ U(W(f), f, c) \text{ subject to } c + pf = I$$

Individuals have an ideal weight, which they would choose if it were costless to achieve and their bodyweight was their only source of utility. However, because losing weight takes time and effort, and food provides direct utility, rational consumers might actually maximise their utility at a bodyweight that is higher than their ideal.

Food has both direct positive effect, through enjoyment and the satisfaction of hunger, and an indirect effect on marginal utility that is negative when the individual's weight is greater than their ideal weight. This is because individuals lose more utility the further they are from the ideal weight. The second part of Ruhm's (2012) dual-decision theory, the affective system will be explained later.

2.3.1.2 Deprivation affects ability to manage weight

Managing weight successfully is based on awareness of weight, motivation to manage weight, and the ability to make good food choices (Drewnowski and Darmon, 2005). Unhealthy foods at present dominate the food supply as they are tasty, energy dense, convenient and cheap. Nutrient rich foods are generally more expensive than calorie dense foods, it is likely that those with higher incomes are less limited in their diets due to being able to afford better food. Because of this, there exists a 'poverty paradox' (Zukiewicz-Sobczak et al., 2014). This is where households with limited budgets can only afford to eat energy dense foods as they cannot afford a higher quality diet, and therefore may not have the resources to manage weight successfully (Drewnowski and Specter, 2004). As gym memberships, exercise equipment and clothing may be expensive, it is likely that those with higher income will also have better access to physical activity. Therefore, it could be that the individual discrepancies in weight-loss intentions and actual weight-loss for those in low-income households are caused by constraints, and not their ability to lose weight, and that individuals that want to lose weight struggle to do so because of a lack of access to the right tools.

Hruschka (2012) outlines potential reasons why low-income populations may be more overweight than higher-income groups. The main reason is that cheaper foods are those with the highest energy density, which leads to overconsumption of energy. It could also be that individuals may be sorted by the educational system and job markets due to bias against individuals with obesity. However, bias in the educational system and in early-career job markets do not account for those who become obese in later life, as these people will not have faced this bias. Another reason presented is that deprived households may be in geographical areas in which there is a low access to healthy food. Drewnowski (2012) and Bimbo et al. (2015) found that having a supermarket in the local area was linked to improved diet quality and a lower prevalence of obesity whilst Zeng et al. (2015) negated this, stating that food deserts have an ambiguous effect on bodyweight. Morris et al. (2013) found a positive and significant effect of food desert intensity on obesity prevalence, but this was only small in magnitude. A third possibility is that there is an association between deprivation and low self-control, which is necessary for managing weight. This could be due to being in stressful situations more often, or the lack of experience with using self-control that high-income individuals might have had through their education. Atella and Kopinska (2014) found individuals who had completed their lower secondary education had a significantly lower BMI than those who hadn’t.

Pan et al. (2012) performed an analytical test of the relationship between obesity and self-reported food insecurity in the United States. It was found that those that had often been stressed about being able to afford nutritious meals over the last 12 months were significantly more likely to be obese than those who hadn't faced the same level of food insecurity. This indicates that despite these individuals being aware that they should be eating nutritious meals, they are unable to because of their economic position. Ailshire and House (2012) found, using large data from the United States, that those in society that were most socially disadvantaged gained more weight than higher social classes over time, and that these differences tended to be larger at a younger age. Guerra et al. (2015) found in a 5.5 year-long cohort study on a sample of individuals from Switzerland that financial difficulties were positively associated with weight gain.

However, this implies that both groups are actively trying to lose weight and low-income individuals are less able. It could be that individuals in lower-income groups attach less stigma to being overweight and have higher ideal body weights than high-income groups. Seward (2014) found that income affected desire to lose weight with those in low-income groups having a lower desire, and less weight loss attempts than those in less deprived groups.

Further research by Drewnowski et al. (2015) found that whilst property values were able to predict obesity, they did not predict 1-year weight change. In their analysis, no measures of socio-economic status had an effect on weight change over a year. This tells us that whilst there is a correlation between deprivation and obesity, this may not affect individuals that are trying to manage their weight. However, this study included a sample of only 444 individuals, with only 291 of these reporting that they were trying not to gain weight over the past 12 months.

Drewnowski and Specter (2004) however state that the relationship between obesity prevalence and low-income is apparent for women, but is less consistent for men. The 2013 Health Survey for England found that there was a negative correlation between household income and obesity, and this pattern was more apparent for women than men (Moody 2014). Whilst there was a correlation between obesity and deprivation by all measures for women, the correlation was only apparent in men for occupation and qualification based measures (Moody, 2014).

As well as having access to more expensive and healthier foods, individuals with high socio-economic status arguably have a larger cost associated with excess weight and poorer health due to their longevity advantage (Pampel et al., 2012). This means that as high socio-economic status individuals tend to live for longer, they have the most to gain from being healthier in each year of their life. This can give more motivation to put time and effort into weight management.

O'Neil et al. (2015) provides an insight into how stress and family support affects weight change. The researchers suggest that economic pressure can affect the access to the food required for a healthy body, which makes it difficult to maintain weight. Stress can also cause depressive symptoms, which can mean less motivation to maintain good health and make good health decisions. The researchers hypothesise that support from a spouse can encourage healthier eating and mediate the effect of stress.

O'Neil et al. (2015) interviewed 702 couples who replied on a scale of 1-5 on how much stress they faced, and how much spousal support they received. They found that economic pressure often caused feelings of stress and anxiety. The researchers found a direct association between economic pressure and poor weight management behaviour for the wives in the sample, but not for the husbands.
However, higher levels of spousal support was associated with poorer weight management behaviour for husbands, but not wives. Couples suffering economic difficulties reported receiving less support from their spouse. The researchers find different relationships between spouses have different effects on weight behaviours. For example, some partners drew attention to weight issues, while some partners bonded over food and share it together.

2.3.1.3 Tighter time constraints make managing weight more difficult

As well as having a budget constraint to restrict choices, a finite amount of time also limits the options of individuals. The 'SLOTH' model explains a time constraint of 24 hours each day to split amongst 5 activities in order to get the maximum possible utility: sleep (S), leisure (L), occupation (work; O), travel (T) and home production (H). Each individual must also maximise their utility subject to a budget constraint, as individuals do not have unlimited spending power (Cawley, 2004).

Equation 2

$$\Delta W = c(F) - f(S, L, O, T, H, G) - \delta(G)W$$

Equation 2 shows that when energy intake, c(F), is greater than energy expenditure, bodyweight will increase. Weight change is a function of how the individual allocates their time during each day, as well as their genetics, G. The individual's metabolic rate is $\boldsymbol{\delta}$, which is also a function of the individual's genetics. We can see that therefore, individual's weight depends on three separate factors – energy consumption, how their 24 hours are spent, and genetics – all of which differ from person to person. Some individuals will enjoy eating, or be comfortable being overweight, while others may not like eating or greatly dislike being overweight. Whilst exercise and eating healthily are recommended to individuals to improve health, people will only do it when it is the best use of their time. Individuals who are very busy will likely place a higher value on each hour of free time as it is scarcer. This could mean that exercising or cooking rather than getting a takeaway for these people is more costly. This of course is assuming that people do not enjoy exercising or cooking. Contrary to this, Sturm and An (2014) found that in the United States the rising obesity prevalence rate coincided with an increase in leisure time. However, there are many other factors that can affect the obesity prevalence rate and this link may not be causal.

Whilst there used to be gender-defined roles, both parents often now work outside the home meaning that home production must now be completed in a shorter space of time after work. This time scarcity results in less free time for leisure and relaxation. Single parents have an even tighter constraint on their time, whilst low-income parents may not be able to afford childcare or eating out – both of which would increase the amount of free time available (Celnik et al., 2012).

2.3.1.4 Society has an effect on individual weight preferences

Dragone and Savorelli (2012) introduce an alternative model of eating behaviour in which the utility of an individual, who belongs to a group (society), depends on two factors: the amount of energy taken in via food consumption, and on bodyweight. Each individual has a different ‘satiation point’, which is the point at which the marginal pleasure from one extra unit of food consumed is 0. If we make the assumption that energy consumption cost no money and provided no calories, a rational individual would eat until the point where marginal utility from food is 0. Therefore, the assumption is made that if an individual eats below their satiation point, they are on a diet, and attempting to lose weight. The authors state that utility from bodyweight is determined in two ways: health, and social desirability. Individuals take the socially desirable body weight into account in decision making as being closer to the desirable body weight provides greater utility than having a weight that is much greater than it. This social cost can be explained by discrimination from peers or discrimination in the work place. If this is the case, those that are not in work may have a lower cost associated with their obesity.

Oswald and Powdthavee’s (2007) theory makes the assumption that the utility of body weight is influenced by the weight and size of the rest of society, and that people change their preferences in response to a change in the average population weight and size (Anand and Gray, 2009). The responses of individuals to this change can then feed back into further society weight gain causing a vicious circle.

2.3.1.5 Limited information and time can lead to poor weight management decision making

Whilst classic economic theory makes the assumption that individuals have perfect information and understanding of this information, this is very simplistic and unrealistic, especially when making food decisions. Often these decisions are made with limited information and limited time to think about the costs and benefits of decisions. Therefore, the collecting and processing of information can be costly to consumers (Grunert et al., 2012).

In situations where time is sparse, for example while waiting in the queue for a meal at lunch, individuals will not have time to collect and process the information they need to make a fully informed decision. In these cases, they will rely on heuristics, which are rules, or habits, that individuals create internally in order to make acceptable decisions quickly (Just and Payne, 2009). Saba et al. (2013) found in an Italian-based survey that respondents with obesity were significantly less interested in nutritional information than the non-obese respondents.

Etile’s (2000) model that makes the assumption that individuals initially do not have complete knowledge about the risks of obesity, and instead learn about the harmful consequences of their actions through their own experience, and the experiences of peers (Sundermacher, 2012). When they experience adverse health consequences, this provides new information to the individual about their health production function, and allows the individual to revise their risk. The equation for Etile’s model is shown in Equation 3 below.

Equation 3

$$\gamma_i(t, HS_{it-1}, X_{it}) = P(\, T_i = t \mid T_i > t, H_{it}, HS_{it-1}, X_{it})$$

Here γ_i represents the conditional probability of behaviour change given a health shock, HS, in period t or $t-1$. X_{it} is a vector of covariates summarising the observed differences at t.

Etile (2000) makes three assumptions regarding health shocks. The first is that the health shock is related to and caused by obesity, and that the effects can be improved by behaviour change. The second is that the individual has the medical knowledge to link this health shock to their own behaviour and habits. The third is that the individual has the knowledge to be able to change their consumption habits and behaviours to achieve a lower risk level (Sundermacher, 2012).

The model predicts that there is a correlation between the decline in the health of the individual and the decision to adopt a healthier lifestyle. Individuals who are obese and who experience a health shock, or have a friend that experiences a health shock, will lose weight in the current or next period. However, in a summary of studies on the effect of health shocks, Sundermacher (2012) found no effect of health shocks on the behaviour of overweight individuals. It could also be the case that the link between overeating and a number of diseases is not understood by consumers. Even if individuals do know their health shock has been caused by them being overweight, they may not have the know how to successfully reduce weight, or, they may not have the willpower to diet successfully.

2.3.2 Theme 2: Time-Preference

Time-preference suggests individuals put a discount rate on events that occur in the future as people have a preference for the present. Because of this preference, benefits in the future are valued less than the same benefit occurring in the future, and a cost in future is preferred to a cost today. Therefore when making a decision, the net present value (NPV) must be calculated, which weighs benefits against costs with future benefits and costs being applied a discount rate. The formula can be found in Equation 4, where r is the discount rate.

Equation 4

$$\mathrm{NPV} = (\text{present benefits} + (\text{future benefits} * (1 - \mathrm{r}))) - (\text{present costs} + (\text{future costs} * (1 - \mathrm{r})))$$

Heterogeneity in people's time-preference is the second theme used to explain the variation in how individuals manage their bodyweight. Time-preference affects how individuals evaluate benefits and costs of weight-related behaviours, such as eating, physical activity, and choices such as weight-loss strategies (Fan and Jin, 2013). An individual's personal time-preference and method of discounting will therefore have an effect on individual's weight decisions and weight trajectory (Richards and Hamilton, 2012).

2.3.2.1 Larger discount rates make weight management more challenging

Exponential discounting assumes each individual has a constant discount rate (Jeffery, 2012). This is rational, as the delay of payoffs provides its own cost as the individual has to wait for them. Choosing a weight that maximises health will only be optimal if the discounted utility of being at optimal weight in future outweighs the present benefit of eating food or not doing physical activity (Cavaliere et al. 2014). It has been suggested that an increase in the average discount rate would lead to a rise in the population's BMI, and it could be that this has been a contributing factor to the increase in the obesity rate (Dodd, 2008). Barlow et al. (2016) found in a systematic review of time-preference literature that there was moderate evidence in favour of a significant link between high time-discounting and the risk of overweight and obesity.

Cavaliere et al. (2014) found a positive and significant relationship between time-preference, which was measured by people's self-report diet related behaviours, and BMI at the 1% significance level. A problem here is that diet behaviours are likely to affect BMI directly. Cavaliere et al. (2014) conducted face-to-face interviews of 240 people across 6 hypermarkets and 12 supermarkets in the city of Milan, Italy. The respondents were asked to answer questions about their height, weight, whether their diet was chosen based on taste or health effects and how often they look at nutritional information before making purchases. Respondents also answered questions covering a range of socio-demographic characteristics in order for these to be controlled. However, the researchers recognised that this time-preference pattern could be caused by a lack of awareness of long-term health effects from obesity, rather than individuals who have higher BMI being more impatient.

Courtemanche et al. (2014) presents the utility maximization problem for weight across multiple time periods in a two-period model. It is assumed that, food consumption, f, provides instant utility, U(f), at a cost of p per unit, and also a future utility, V(f), shown in Equation 5. Individuals' weight in the following period is a function of food consumption, w=g(f), with g increasing in f. Each consumer then receives a future utility from their weight, V(w) subject to the individual's discount factor, δ.

Equation 5 shows that the utility in the second period is a function of the quantity of food consumed in the first period. Second period utility is decreasing with excess food consumption, as increased food consumption in the first period results in an increase in weight which reduces utility.

Equation 5

$$\mathrm{V(f) \equiv V^{*}(w) = V^{*}[g(f)]}$$

shows the maximisation problem faced by each person (Courtemanche et al.,2014). Here, individuals maximise utility based on their current utility, cost and future utility, subject to a discount rate.

Equation 6

$$\max_{\mathrm{f}} \mathrm{U(f) - pf + \delta V(f)}$$

In the first period utility is increasing and concave in food consumption, as food intake is enjoyable, and each additional unit of food intake provides less utility than the last. The model assumes that when an individual has a higher weight than ideal, the second period utility is decreasing in weight.

The main prediction of time-preference theory is that those consumers with a less strong preference for the present should theoretically have a lower weight. As these individuals have a lower discount rate, the future utility from being at a lower weight has been discounted less and so is more likely to outweigh the benefit of food consumption in the present period. This yields a lower equilibrium weight (Courtemanche et al., 2014).

Courtemanche et al. (2014) investigated the relationship between time preferences, economic incentives and BMI using large American databases of prices, saving behaviour and BMI in order to test this theory. The researchers again found strong evidence of a correlation between time-preference and BMI. Impatience was associated with high BMI across a wide range of specifications.

2.3.2.2 Immediate risk adds to incentives to manage weight

Time-preference theory predicts that the people that behave in the most risky fashion, and are in the poorest health to have the highest discount rates. This is because these individuals have a higher risk of death in each period and so as the future is more uncertain, any benefits or costs in the future are discounted more. Therefore, the present is valued relatively greater by an ill person than an individual with a lesser health risk (Richards and Hamilton, 2012). Another prediction of time-preference theory is that older people will have a greater motivation to be at a healthy weight, as the negative health effects from obesity generally occur later in life. Therefore for negative health effects, younger individuals apply a larger discount (Grunert et al., 2012). Richards and Hamilton (2012) surveyed 82 undergraduate students to find out their time-preference valuations in 50 separate scenarios. The researchers found that obesity was positively related to the discount rate of an individual. It was also found that those who engage in risky behaviour discount at a higher rate. This relationship could act in both ways. It could be that the individual's risky behaviour causes the higher discount rate as they have a higher chance of hazard in any given period. However, it could also be the case that individuals act in a risky fashion because they have a high discount rate, and value the utility gained from their risky behaviours relatively higher than the future health effects. One limitation of the Richards and Hamilton (2012) analysis is that the sample of undergraduates may not be a proportionate representation of the whole population due to this population being younger and more educated than the average person. Another problem is that is difficult to put a value on a person's discount rate, and the rate will differ depending on whether it is regarding money or health.

2.3.2.3 Time-preference can be irrational with preferences being inconsistent over time

There is also the theory of hyperbolic discounting, which is irrational. This is where individuals do not discount at a constant rate, instead changing their preferences depending on which time period they are in. Hyperbolic discounters can irrationally place immediate gratification and short-term impulses ahead of long-term goals (Fan and Jin, 2013). Because their preferences are irrational and change with time, often individuals will make decisions in the present that go against their long-term goals and their utility maximisation plan. This results in individuals viewing their past decisions as mistakes. Fan and Jin (2013) found in a study of the US that individuals that were overweight or obese showed significant differences between their intended weight-loss plans and their actual eating and activity behaviours. This shows that individuals who are obese may set out with good intentions, but as their preferences change depending on what period they are in, may not stick to their initial goal.

With hyperbolic discounting, individuals underestimate the impact of their actions today on future consequences and do not discount at a constant rate (Richards and Hamilton, 2012). Hyperbolic discounters strongly discount values with a short delay whilst applying smaller discount rates for longer delays. For example, if a hyperbolic discounter is offered £100 today or £110 next year, it is likely that they will take the £100. However, if the individual is offered the choice between £100 in 10 years, or £110 in 11 years, a hyperbolic discounter would likely take the second option despite the fact that in 10 years they will be in exactly the same scenario as they were in the first question. This theory tries to explain how individuals may not discount at constant rates, and why individuals believe that they may have more self-control in future. This theory can be used to show why people often decide that rather than starting a diet now, they will start the diet at some future time-point such as next week or on the 1st of January (Richards and Hamilton, 2012).

2.3.3 Theme 3: Habits and Self-Control

2.3.3.1 Stronger habits increase the cost of weight change

One problem affecting weight management behaviour, and leading individuals to gain weight is that over-consumption of food and drinks and sedentary behaviour may be habitual. Dragone (2009) states that due to habits, and individuals finding that what they are used to is the easiest choice, a new level of food intake cannot be chosen without cost. This is because to change a habit, the individual will have to evaluate new options which requires both time and effort. Some individuals find these habits more difficult to change than others, and so for them it can be very costly to change their behaviour in regards to weight management. It is assumed that the cost to utility is increasing with the magnitude of change in habits – the more drastic the change, the harder it is to maintain.

Dragone's (2009) model predicts that the optimal weight trajectory depends on the individual's strength of habits, which is measured as the marginal effect on utility from changing the food intake level. When the marginal disutility from changing the food intake is low, an individual can rapidly switch to the steady state amount of food consumption, as the expected utility gains achieved at the level can overcome the adjustment cost. As the strength of habit increases, it is optimal to slow down the rate of convergence to the steady state level of food consumption in order to reduce the disutility from changing consumption habits.

Dragone's (2009) model implies the agent is so slow at adjusting their eating behaviour that they cannot stop suddenly at their optimal weight and keep losing weight and continue losing weight past the optimal weight. Eventually the individual will realise their weight being below optimal weight is again having a detrimental effect and they will put weight back on. This theory hypothesises there is an oscillatory pattern present in chronic dieters.

2.3.3.2 Habit change most successful when habits are replaced with an alternative

Individuals will spend time doing activities that are relatively more reinforcing to them, and the more the individual performs this activity, the more reinforcing the activity becomes (Buscemi et al., 2014; Jeffery, 2012). The activities that provide the most reinforcement are habitual, and as they are so reinforcing, they are automatic, require little thought, and therefore difficult to break. Individuals who tend to value food over alternatives will have this preference reflected in their resource allocation, and will therefore be more likely to be overweight. Reducing the consumption of high valued goods is facilitated by engaging in reinforcing substitute activities.

Buscemi et al. (2014) performed a study to test this theory on a group of 200 individuals that were overweight or obese aged 21-65 who had no heart problems or troubles moving, and were attempting no alternative weight loss methods. The participants were prescribed cognitive, diet, and physical activity meetings for a year-long period, where the meetings were weekly for the first 6 months, and bi-weekly for the next 6 months. It was found that there was a decrease in food reinforcement relative to non-food reinforcement, and this was associated with a decrease in BMI. Researchers found that at baseline, the average participant derived 37.9% of reinforcement from food-related activities. This had decreased to 30.3% at 6 months and gone back to 32.1% at 18 months. Individuals had lost on average 10.9% of their initial weight after 6 months, and 9.7% at 18 months, showing that much of this weight loss had been maintained, but due to reinforcement falling, some of the weight loss had been regained. It could be the case that this weight is put back on as individuals need to replace the reinforcement received from the classes, and replace it with food.

Xiameng et al. (2016) performed a similar test whereby individuals were surveyed at both the start and the end of a behavioural weight loss intervention. The participants were asked to answer 4 questions, on a 0-6 scale about their life during the 12 weeks of the intervention. They rated how exciting, how boring and how interesting their life had been, and how much they felt they had grown as a person. The researchers found that individuals answered significantly more positively about their lives after the intervention, and that this increase was associated with better adherence and weight loss. This helps to back up Buscemi et al.'s (2014) theory of reinforcement, and it could be that those individuals that lose the most weight initially are able to continue after the intervention due to their improved happiness after weight loss.

2.3.3.3 Individuals will stop their weight management once initial losses have been compensated

Djawadi et al. (2014) presents a framework of medical non-persistence, to explain why individuals that decide to diet often stop their efforts early. Often, these individuals are rationally better off continuing with their diet but do not comply with it as they lack to self-control to do so. The reason for this is that individuals are not perfectly rational, and in this framework, individuals value their gains and losses relative to a reference point, with the losses being valued more than gains. Lim and Bruce (2015) found in a study of 67 individuals that people displayed a stronger dislike of weight gain than their like of weight loss. Lim and Bruce (2015) found in a study of 67 individuals where individuals had to complete two decision-making tasks for weight loss, that people displayed a stronger dislike of weight gain than their like of weight loss, which shows that this stronger dislike of losses is also found in weight change. This study is limited by the small sample size.

There are three phases of assessment involved in the framework: the phase of invasion, the phase of high persistence, and the phase of discontinuation. In each time period, the individual makes one of two choices: to invest in health by continuing with the weight management (the cost of persistence), or by not investing, and discontinuing with the programme, which maintains the current health state, but gives a higher risk of disease.

The theory predicts that individuals will in fact discontinue their treatment before the course is over. Study participants incur costs during the invasion phase as they have to put in the effort to go to classes and learn how to lose weight, without receiving any immediate health gains. Due to this, there is a feeling of loss as this effort causes a loss of utility. However, as people are assumed to be loss averse, once these losses are compensated for, the individual has no incentive to continue with their weight management.

To test Djawadi et al.'s (2014) theory, 107 individuals partook in an investment game with two stages. The first stage is to induce the feeling of loss through time and effort of completing a task and receiving only 2 talers (the currency in the study) instead of the promised 8, so it feels like a loss of 6. The second stage is a lottery that mimics health investment for 12 time periods. Participants choose between a safe lottery, which has a 95% chance of paying out 2 talers, and a 5% chance of paying -1 talers, and a risky lottery, which has a 70% chance of paying 2 talers and a 30% chance of paying 0 talers, in each period. If the individual loses the lottery, they are unable to play again. Despite the rational optimising prediction being to continue with the safe option until period 10, the majority only play until period 7, which is the period where losses are compensated for, and in line with the theory prediction.

The evidence from the investment game backs up the framework of medical non-persistence as individuals in the test play the safe option until their losses are compensated for. After this, individuals start taking risks in the game as the marginal benefit of continuing with the safe option falls. The researchers suggest that interventions should take into account improvements that take persistence behaviour into account.

2.3.3.4 Self-control problems can be countered with mechanisms

The second half of dual decision theory, mentioned earlier, is the affective system, in which decisions are influenced by quick acting processes, and are often automatic in response to cues and stimuli (Ruhm, 2012). The affective system is influenced by food characteristics and stimuli according to a motivational function that varies from person to person. Dual decision theory predicts that as the affective system does not account for the consequences of future weight, the costs of consuming excess energy are not fully accounted for, and so calorie intake and weight will likely be above optimum. In this case, individuals may actually have their utility raised by incentives that reduce the influence of the affective system.

Sophisticated agents know that deliberative processes in future periods can be interfered with by the responses of the affective system and so individuals may take steps to limit the options available to the affective system, and the impact it can have (Dodd, 2008). People will employ strategies to raise time-costs in order to avoid self-control problems. These could be things like sticking to a set of rules, keeping unhealthy foods out of the house, or buying in smaller quantities. Conflicts between the two systems are resolved through intermediate levels of food intake, with the relative power of each system varying by individual (Ruhm, 2012). Those with greater self-control have relatively weaker affective systems compared with those that have less self-control.

Ruhm (2012) tested this theory on large United States national health databases. It was found that whilst BMI has risen rapidly overtime, the probability of weight loss attempts at any given BMI is unchanged, which suggests that ideal weight has not risen, and that weight gain instead reflects mistakes induced by the affective system. This increase in mistakes could attribute itself to the improved ability of the food industry to manipulate the affective system and create demand for their products.

A distinction is made between consumers based on whether they are naïve or sophisticated regarding their understanding of how their time-preference will affect their self-control in future. Naïve consumers do not realise that their preferences will change, and believe that they do not have a time-preference. Sophisticated consumers on the other hand understand how time-preference will affect their future preferences perfectly (Dodd, 2008; Fan and Jin, 2013). As naïve consumers do not understand their lack of self-control, they may overeat in the current period because they expect that they will have the self-control to forgo excess food consumption in the next period, and then, as they have incorrectly anticipated their future self-control, will not be able to stick to their weight management goals (Rosin, 2012).

Sophisticated individuals are able to look for mechanisms that will adjust payoffs and give them more incentive to stick to their weight plan (Dodd, 2008; Fan and Jin, 2013). Jeffery (2012) states that financial incentives should theoretically improve weight outcomes whilst removing these rewards should damage outcomes. If we assume that individuals can alter their own incentives via strategies such as dieters betting on their weight loss, so that the potential gain from their bet compensates the utility lost from discounting, then we could see improved outcomes. If individuals sign gym contracts, so if they don’t continue attending their gym they will have wasted money on an un-used membership, the commitment of paying could act as an incentive to attend. Hashemi et al. (2015) found that more immediate forms of payment (such as an upfront fee rather than monthly payments) caused a significant increase in participation in a weight loss programme.

Fan and Jin (2013) aimed to test the difference in self-control capabilities between individuals with obesity and individuals of normal weight. They used 4 large US databases to do this. Fan and Jin (2013) discovered that individuals who are overweight or obese felt they were less able to control their lives through self-motivation, and that this group of people exhibited a lower degree of self-control that was associated with poor eating and exercise behaviours. However, the researchers assume that all individuals have access to healthy foods and physical activity, which is a limitation as individuals in more deprived areas may not have the same access as those in less deprived areas.

2.3.3.5 More weight loss attempts makes future weight loss more difficult

Rosin (2012) presents a model where it is assumed people's dislike of being overweight is learnt at the moment when they first attempt to lose weight. In Rosin's (2012) model, individuals plan out a certain time period, for example one year, and in that time they state the fraction of that period that will be spent dieting. The negative effect on utility in the period increases with diet duration and the extent of the energy deficit whilst dieting. This is due to the extra effort put into dieting. Here, the loss of utility falls at increasing rates with both the size of the energy deficit and the length of the diet. This is because individuals lose willpower during their diet and eventually the loss to utility they face from dieting is too great and the individual stops. Rosin (2012) also states that dieting is an increasing function of initial bodyweight, which is intuitive as those that have a highest body weight will have the most weight to lose. Therefore these individuals have a higher disutility from their weight, as they are likely to be further from their ideal weight.

Rosin's (2012) model predicts the extent of dieting, in terms of both energy deficit and duration, is a decreasing function of the effort exerted in dieting, the strength of social norms and metabolism. First, because a strict diet requires more effort, it therefore has a larger negative effect on utility. Individuals will therefore generally continue on a strict diet for a shorter amount of time than they would if the diet was less strict. The strength of social norms refers to the extent to which society has an opinion on obesity. If the ideal weight set by society is higher, then individuals will not diet for as long, and if the ideal weight is lower, then individuals will diet for longer. A faster metabolism reduces the duration of diets a faster metabolism burns more energy. The model also predicts that individuals that have had more diet attempts will have a shorter diet duration.

2.3.3.6 A higher stock of past consumption increases the utility derived from present consumption

In Becker and Murphy's (1988) theory of rational addiction, individual utility depends on the amount of past addictive consumption (where past addictive consumption is consumption that increases the utility of present consumption). For example, according to the theory, an individual that has consumed a greater amount of cigarettes will have a greater addiction and gain more utility from an additional cigarette in comparison with a lighter smoker. The theory shows that people will quit their addiction if discounted costs are higher than the discounted benefits of continuing. Rational addiction assumes time-consistent preferences, and predicts an overconsumption of energy which is consistent with optimising economic behaviour (Richards and Hamilton, 2012). With rational addiction, obesity is rational if you make the following two assumptions: overeating is the main cause of obesity, and that compulsive overeating, is an addiction. It is the general consensus that overeating is the main cause of obesity, but whether compulsive overeating is an addiction is questionable. It could be that some people are addicted to certain types of foods (foods high in sugar or fats) which could result in overeating. Whilst overeating can be stopped, it is not possible to cut out food entirely as it is required for sustenance. Therefore if it is an addiction, dealing with it is different to dealing with other addictions (Sundermacher, 2012). If the assumption is made that an individual with a higher bodyweight or BMI has a higher stock of past consumption, then rational addiction theory would lead us to believe that this individual would have a greater level of addiction, and therefore would find it more difficult to reduce their calorie intake and manage their weight successfully.

2.4 Discussion

Three underlying themes came forward in the papers selected for inclusion: rational behaviour, time-preference, and habits and self-control. Rational choice and the exponential discounting part of time-preference are based in economic theory whilst hyperbolic discounting and habits and self-control are generally behavioural economic theories. Each theory attempts to explain weight management behaviour and discusses how human decision making may not always optimal for achieving a healthy weight.

The rational choice theme involves theories about weight decisions regarding people having an equilibrium weight (a weight that optimises utility), that is higher than their ideal weight (the weight the individual would choose if achieving that weight were costless). This is because utility is derived from more than just weight, and so the utility maximising weight will not necessarily be the individual’s ideal weight. For an individual to maintain a weight below equilibrium, the individual may therefore have to eat at below their utility maximising level of food consumption, or perform more than their utility maximising level of physical activity. As individuals are assumed to be utility maximising, maintaining the ideal weight would be sub-optimal. A limitation of the rational choice theme is the assumption that individuals have full information and rationality, which doesn’t explain why individuals may attempt to go on a diet and fail to lose weight. In a real life setting individuals may not look at the number of calories in their food, and in restaurants often the caloric content of the meals is not listed at the point of purchase. As well as this individuals will also have limits on how accurate their knowledge of the number of calories burnt when exercising, their own metabolic rate and the risk factors of different diseases they face at different BMIs. Similarly, individuals are not always rational with people often choosing to eat a chocolate bar during a ‘moment of weakness’ when they know it will hamper their long-term goals and be a decision they regret. Whilst this theme is intuitive it does struggle to explain some behavioural reasons as to why individuals may not be able to manage their weight successfully.

The time-preference theme discusses the theory that utility received in the present period provides relatively more value than utility received in a future period. The theory tells us that the majority of people value the present more than they value something that will occur in the future, and so apply a discount rate onto any future utility. Because increased body weight is a long-term effect, the utility gained from successfully managing weight and being thinner is discounted, whereas the utility from food, and disutility from exercise, occurs in the present, and is therefore not applied a discount. As the utility from managing weight is discounted, this provides a disincentive for forgoing the present utility benefit of food and not exercising. Hyperbolic discounting theory tells us that individuals can make irrational choices, as their preferences are inconsistent and change depending on which time period they are in. Inconsistent preferences can mean that despite individuals believing that in the long-term managing weight is the way to optimise utility, their preferences change in the short-term and they believe their utility will rather be optimised by over-eating – a decision which is then regretted in the next period. This theory is intuitive and explains why some individuals often act irrationally and regret their decisions when attempting to manage weight. Time-preference theory has been empirically proven and is intuitive and so discount rates must be involved in any framework coming from this review.

The final theme is self-control and habits, which describes theories relating to how the behaviour of many can be automatic, subconscious and not always utility maximising. This is because people are habitual and prefer to stick to what they know. This means that despite a different lifestyle choice being more satisfying in the long-term, such as losing weight, the initial cost of changing habits is too large for the person to be interested in changing them. If we consider an individual who habitually orders takeaway every night without concern for managing their weight and drives to work every day, it may be difficult for them to change their habits and begin allocating more of their time into cooking meals each evening and walking to work each morning. This of course would be incorporated into utility as a person may derive more satisfaction from a takeaway that preparing their own meals, but it is likely that the initial change is difficult to make and maintain. Habitual choices and responses require very little thought or effort, so an individual may revert back to what they know rather than constantly weighing up the costs and benefits of potential alternative options. The cost of collecting and processing new information, in terms of both money, time and cognition, tends to deter individuals from making the effort to learn about how to successfully manage their weight. A lack of self-control can be caused by rational addiction or the affective system. Despite people believing that the decision they are making damages their long-term goals, they cannot resist the current satisfaction, and make a sub-optimal decision resulting in reduced overall utility.

A strength of the research is that the initial search was comprehensive and used many terms relating to each of the four categories. A further two searches were then added by combining the search terms in alternative ways and searching only the titles. This was in order to ensure that all key papers that met the criteria were identified.

Each of the 15 theories selected for use in the creation of a new theoretical framework of weight management are summarised below, along with the hypothesis that each theory makes:

Rational Choice:

(1) As an individual's body weight is not the sole source of utility for the person, an individual may rationally choose to be overweight if it means gaining more utility from other areas such as overeating or being sedentary. The cost to an individual's utility from being overweight increases with extra pound the individual is over their ideal weight.

(2) If an individual has a low-income, they will be less able to afford healthy foods (calorie-dense foods are cheaper) or have access to healthy foods (limited range of healthy food in neighbourhood shops). It could also be the case that there is limited access to exercise as gym memberships and athletic equipment cost money.

(3) Each individual faces a time constraint as each person only has 24 hours in a day. If a person has a full-time job and a family, it may be difficult for them to find the time to exercise or cook home-made meals, and so the opportunity cost of any remaining hours of their day will be larger.

(4) Individuals in households that face more economic stress may have poorer weight management behaviours which can be offset by having a supportive partner.

(5) Society has an effect on individual weight preferences as bias and discrimination against being overweight has an effect on individual utility.

(6) Provision of new information can impact on an individual's perception of risk, and therefore affect their decision making, as long as that information is processed by the individual. Individuals that have had a health shock (heart attack, stroke, diabetes) from their condition will have better knowledge about the risks of being obese and therefore be more likely to try and change their behaviour.

Time-Preference:

(7) Individuals who place a greater value on the present are more likely to be overweight; this is due to the lower relative weighting they put on the disutility from future weight gain.

(8) Individuals who face a more immediate risk to their health will be more motivated to reduce this risk.

(9) Irrational hyperbolic discounters are likely to make decisions in the short-term that are inconsistent with their preferences (such as overeating or not attending a class when their goal is to lose weight) as their preferences change depending on what time-period they are in.

Habits and Self-Control:

(10) Individuals with weaker habits are more likely to be able to adjust their lifestyles in order to manage their weight, as when they attempt to change their habits they incur lower disutility.

(11) Individuals who replace their eating with another activity that they find to be reinforcing will help them stick to their diets.

(12) Individuals participating in an intervention will continue with the intervention until all losses are compensated for (the benefit of the programme has compensated the cost and effort of attending).

(13) Individuals generally have self-control problems, and those that are sophisticated and aware of the problems they will face in the next period are able to limit the impact that their lack of self-control can have on their weight management. This can be done by limiting future choices and making commitments such as not bringing unhealthy foods into their house or purchasing a gym membership. Therefore it is less likely that sophisticated individuals lapse back into old habits and regain weight.

(14) Individuals who have attempted to lose weight in the past are likely to find each successive diet more difficult than the last.

(15) Rational addiction theory states that those with a higher stock of past consumption will gain more utility from consumption in the present, therefore making it more difficult to reduce consumption and manage weight.

Using the findings from this review, a new framework will be constructed in Chapter 3 to form hypotheses regarding weight management behaviour. This framework will then be tested using a weight management programme as a case study and then used to predict weight loss and weight trajectories in the long-term depending on individual characteristics and demographic information in Chapter 5.

Chapter 3: The Theoretical Framework of Weight Management

In the previous chapter, theories of weight-management and hypotheses regarding the influencers of weight-management behaviour were identified. The next stage, presented in this chapter, was to use these theories to create three frameworks of weight-management based on the themes of rational choice, time-preference and habits and self-control.

The rational choice framework includes theories based in neo-classical economics and discusses rational decision making based on the premise that individuals aim to maximise utility and bodyweight is a source of utility. The time-preference framework will involve theories regarding how individuals assess potential future events and discount these future values, which can be done either rationally or irrationally. The habits and self-control framework involves behavioural economic theories which can be applied to weight management to explain how individuals may behave in regard to weight and why individuals may not always act with full rationality.

3.1 Rational Choice Framework

Equation 7 shows that utility is dependent on a combination of the utility from the individual's bodyweight (W_i), their consumption of food (F_i) and all other consumption (C_i). Individuals must choose a combination of these three factors to maximise their utility (U_i). Utility from an individual's bodyweight weight is derived from three areas – social desirability (s) as it is assumed society prefers people of a healthy weight, health (h) as obesity contributes towards poorer health, and bias (b), as individuals with obesity are likely to earn less in the workplace (Puhl and Heuer, 2009; Reichert, 2015[2]). An individual derives a greater amount of utility from each of these three factors the closer they are to their ideal weight, which in turn increases the total utility received from bodyweight. Individuals gain utility from food as people both enjoy the taste of their food and the satisfaction of their hunger. Individuals also gain utility from

[2] Reichart (2015) found that losing weight increased employment prospects for women in the UK but not men.

all other consumption as weight and food are not the only sources of satisfaction.

Equation 7

$$U_i = UW_i(s,h,b) + UF_i + UC_{,i}$$

Individuals maximise their utility subject to a budget constraint (I_i), shown in Equation 8, as people do not have an infinite amount of money. This means that with no limit to spending, equilibrium weight may be different to when a limit on spending is considered. As well as facing a budget constraint, individuals also face a limit to their time (t), shown in Equation 9. The time constraint is shown as a 24 hour period where the hours are split across 5 different activities: sleep (S), leisure (l), occupation (O), transportation (T), and home production (H) (Cawley, 2004).

Equation 8

$$C_{C,i} + C_{F,i} = I_i$$

Equation 9

$$t = S + L + O + T + H = 24\,\text{hours}$$

These equations set out why an individual may rationally choose to be overweight, as bodyweight is not the only source of utility (Richards and Hamilton, 2012).
The rational choice framework explains why individuals may rationally choose to be overweight, and is formed using the theories in the rational choice section in Chapter 2. Equation 10 shows the theoretical framework of rational choice explaining weight management. The framework shows weight change is determined by a number of factors. The first is the difference between the individual’s current weight and the weight that provides the most utility were weight the only source of utility – the ideal weight (W_{Ii}) as this shows how much excess weight the individual has according to their own personal preferences. The next two are the budget constraint (I_i) and time constraint (T_i), which reveal how much money and free time the individual has to invest in their weight management. How supportive the individual’s partner is (PS_i) is another contributing factor towards weight change. The level of bias and discrimination (B_i) the individual faces also contributes to weight change as

those who receive the most should have the most motivation to lose weight, according to theory, although there may be negative psychological effects that make managing weight more difficult (Lim et al., 2017; Jung & Chang, 2015). The final contributing factor is how knowledgeable the individual is about weight management (K_i) and the risks of obesity.

Equation 10

$$\Delta W_i = f((W_i - W_{Ii}), I_i, T_i, PS_i, B_i, K_i)$$

3.2 Time-Preference Framework

The time-preference framework argues that individuals value outcomes that are in the future differently to those in the present. Equation 11 shows that an individual's utility comes from the utility an individual gains in the present period ($U_{i,t}$) plus their utility in the second period ($U_{i,t+1}$) and so on, with each period being discounted at a constant rate, with periods further into the future being discounted more (Jeffery, 2012). Again the assumption is made that individuals derive utility from their weight, consumption of food, and other consumption. However, hyperbolic discounters, who discount irrationally, do not keep a constant discount rate – theirs will vary depending on which time period they are in (Fan and Jin, 2013).

Equation 11

$$U_i = U_{i,t}(W, F, C) + d_i(U_{i,t+1}(W, F, C)) + \cdots + nd_i(U_{i,t+n}(W, F, C))$$

Equation 12 shows the theoretical framework of weight management formed using theories identified in Chapter 2. The first contributing factor is the individual's personal discount rate (D_i) as those who have higher discount rates are less concerned about the future impact of their decisions relating to weight management in the present. The second factor is the probability an individual suffers a health shock (H_i) in the next period as those who are more likely to suffer a health shock soon will have a larger incentive to change their behaviour than those who do not have a high probability of an imminent shock. The final factor in time-preference affecting weight change is whether or not the individual is a hyperbolic discounter (HD_i=1), as hyperbolic discounters have irrational preferences and will often act in ways that contradict their long-term weight management goals.

Equation 12

$$\Delta W_i = \mathrm{f}(D_i, H_i, HD_i)$$

3.3 Habits and Self-Control Framework

The habits and self-control framework uses theories from behavioural economics to explain what influences individuals' weight management decisions. In this framework, not only does the individual gain utility from bodyweight, food and other consumption, but also from maintaining their habits (hab), and the lifestyle they are used to (Dragone, 2009). Equation 13 shows the utility function.

Equation 13

$$\mathrm{U_i = U(W, F, C, hab)}$$

Equation 14 shows the decision making process that influences weight change. The framework shows that the total amount of weight change depends on the individual's self-control (SC_i). These self-control problems can be countered by investment in the programme (inv_i) which is a combination of time, effort and money, as personal investment provides more commitment. Whether or not the individual makes this commitment is dependent upon whether the individual is sophisticated (sop_i=1) about their self-control issues, and has the foresight to alter their payoffs in order to keep to their weight management goal. Self-control can also be improved by replacing over-eating with an alternative activity (alt_i=1). The strength of weight management habits will also affect weight change as those with strong habits are likely to revert back to their bad habits more quickly. According to theory, those with poor weight management habits are likely to have had a larger number of past diets (pd_i) and a larger stock of past over-consumption (poc_i).

Equation 14

$$\Delta W_i = SC_i(inv_i(sop_i), alt_i) - hab_i(pd_i, poc_i)$$

3.4 Summary

This chapter has provided three frameworks for theories of weight management according to the themes set out in Chapter 2 – rational choice, time-preference and habits and self-control. These theoretical frameworks illustrate the influencers of weight-management behaviour and can therefore be used to form hypotheses regarding weight-change according to individual characteristics.

The next section will introduce a case study of the weight-management programme Slimming World, and a dataset that has been provided for the purpose of this PhD. As many of the influencers involved in these frameworks are either unobservable, or not collected by weight-management programmes, proxy variables will need to be identified to act as substitutes. Once these proxy variables have been identified, regression equations will be developed based on the equations described in this chapter and relationships between these variables in weight-change quantified.

Chapter 4: The Slimming World Programme and Dataset

Chapter 3 set out theoretical frameworks that might be applied to predict weight change. In order to empirically test the hypotheses proposed within the frameworks, data from a weight management programme, Slimming World, will be used. Before the dataset is presented and described, Slimming World will first be introduced, and the Slimming World programme will be discussed in detail. This chapter will provide an overview of the weight management programme and the dataset that will be used to undertake the analyses.

4.1 Slimming World

Slimming World is a UK based company that aims to help people achieve their weight loss goals. The company was founded in 1969 and regards itself as “the most advanced slimming organisation in the UK” (Slimming World, no date a). The company has >16,000 groups which are run by >4,500 consultants. These groups comprise of 900,000 members attending Slimming World classes every week. As well as offering classes, Slimming World has a website and magazine which feature weight loss tips, weight loss stories from members, and recipes. For individuals who want to lose weight but are not able to attend classes, Slimming World offers an online membership which offers the same advice as the standard programme.

4.1.1 The Slimming World Group Programme

Slimming World’s weight management programme begins with what is recommended to be a 12-week weight loss programme, and comprises of group classes, which vary in size, where members are first weighed and then offered advice and support regarding eating, cooking, physical activity and psychological tips to make dieting more manageable. There are three support mechanisms– a ‘food optimisation’ plan, ‘IMAGE therapy’ and ‘body magic’. Each is described below.

Classes begin by each member either paying their fees or redeeming a SWoR voucher at a desk occupied by members of the group that have volunteered to assist the group leader. After registering, each individual is weighed, with their weight then being recorded by a consultant. Members can then tell their consultant whether or not they would like for their weight to remain private from the rest of the group and either stay or not stay for the IMAGE therapy part of the class.

The Slimming World programme is based around a food optimisation eating plan which is centred on eating foods that are filling and are also low in energy density (Slimming World, no date b). The food optimisation plan takes into account the individual's preferences towards food, and adapts to their lifestyle and budget, which makes the plan more convenient for members to adapt their eating habits and to lose weight. In the basic plan, free-foods – those that are low in energy and filling can be eaten without being counted and there is no limit on the quantity. These foods include fruit, vegetables, pasta, potatoes, fish and lean meats. Healthy extras are additional foods that allow a healthy balanced diet, items such as bread, milk and cheese. Foods that are typically regarded as unhealthy are labelled as 'syns' in the Slimming World programme. These include crisps, chocolates and takeaways. Members are only allowed a limited number of these each day; the number is dependent on their weight and gender, with men being allowed more.

At Slimming World classes, the group engages in IMAGE therapy. This is a group discussion lead by the consultant with the aim of informing individuals, providing support, and ultimately adjusting individual behaviours in regards to weight loss. The support provided by consultants involves self-monitoring of feelings and emotions, visualisation techniques, evaluations of the positive and negative effects of actions, and personalised eating plans. Individuals in the group can discuss strategies that they find useful for helping them deal with cravings, and ways to make healthy meals (Slimming World, no date c).

With regards to physical activity, Slimming World promote changing lifestyles to incorporate physical activity through their 'body magic' plan, which focuses on giving members healthier routines, and exercise that the individuals enjoy (Slimming World, no date d). The body magic programme encourages members to engage in physical activity outside of classes in their own time. The programme recommends for members to start out doing light exercise and build up their activity levels over time when they are comfortable with more rigorous exercise. Members receive a body magic booklet which includes ideas and help with how to start and how to set goals to improve. This is in line with the Department of Health’s public responsibility deal, where Slimming World have pledged to encourage physical activity in each member’s daily routine (Slimming World, no date e; Department of Health, 2013).

Classes, which usually last around an hour are led by the consultant in a discussion scenario. All consultants are former members of Slimming World and receive regular formal training at the Slimming World headquarters.

4.1.2 The Cost of the Programme

Slimming World has multiple entry routes into the group programme with the financial cost and number of sessions varying by entry method. The standard entry method consists of an initial joining fee of £10 and then a further £4.95 each week (Slimming World, 2019). An alternative to this is to use one of many discount vouchers found in various magazines. These discounts can come in the form of a waived join fee or having the first week free. Slimming World also offer a pre-payment deal in which the first 6 sessions can be purchased for the price of 5, or the first 12 can be purchased at the price of 10. This package deal is called a ‘countdown’.

As well as joining by paying for classes people in some areas of the UK can be referred to the Slimming World programme by a GP through the SWoR scheme. SWoR began in 2000 in partnership with Southern Derbyshire Health Authority. The cost of the programme is paid for by the NHS and subsidised by Slimming World (Slimming World, no date e). Referrals to Slimming World come in the form of a voucher that can be redeemed for 12-weeks of classes. SWoR reduces the financial barrier to joining the Slimming World programme as those who are referred avoid the weekly payment of £4.95 and the £10 initial joining fee. Individuals who receive vouchers to attend Slimming World classes for free are expected to attend all 12 sessions that have been funded by the NHS, but not all individuals referred fully engage with the programme. For those on the referral scheme, after the initial 12-week period they can choose to continue being a member of Slimming World at their own cost or request more vouchers. More than 210,000 patients have been referred to Slimming World in the last 13 years (Slimming World, no date e).

If an individual is within 3lbs of their target weight then they attend for free, for as long as they stay within 3lbs of their target. Targets are flexible and can be changed by the member at any point – usually when the member approaches their original target.

4.1.3 Slimming World as a Case Study

Slimming World has been chosen as an appropriate case study for a weight management programme as it fits NICE guidelines for an effective weight management programme. NICE recommendations include that programmes should be multi-component (focus on each of diet, physical activity and behavioural change), developed by a multi-disciplinary team, have staff trained in delivery, focus on lifestyle change and have regular meetings (NICE, 2014). The Slimming World programme meets all these recommendations.

4.2 Data

The dataset used to empirically test the hypotheses proposed within the frameworks was taken from a cohort of all Slimming World members who joined the programme between 1st January 2014 and 31st December 2014. A sample of a full calendar year was used to avoid any seasonal spikes, such as at New Year or before summer. Analysis was performed in STATA 13.1 (StataCorp, 2013). A total of 692,945 Slimming World members were included in the dataset. These members have a mean age of 42.70 years and 95.37% are female. The average Slimming World member in the cohort enters the programme with a BMI of 33.31kg/m^2 which means the average member is classed as obese.

Slimming World provided attendance data for 24 months for each individual from the date of their first attendance. As the first attendance is regarded by Slimming World as being before the intervention, it is referred to as 'week 0' of the programme. The dataset includes this baseline week and a subsequent 105 weeks of attendance data.

As the quality of data stored by Slimming World has improved over time, having a recent time period was necessary to improve the quality of the study. Over time Slimming World have collected more variables to allow research into the programme to be more informative. In addition, tablet computers have been given to consultants to enable weights recorded at each session to be fed directly into the Slimming World database and reduce the rates of input errors and missing data. However, another requirement of the dataset for this study is that there is the potential for a lengthy amount of follow-up. If a more recent year than 2014 was chosen, the maximum follow-up for the study would have been limited to less than 24-months. Therefore the members joining in the year 2014 was chosen as a balance between good quality data and a substantial amount of time for follow-up.

Slimming World collect data from all the participants in their programme. This includes demographic information including age, gender, where the individual lives, whether the person lives with a partner or children, employment status, and whether the individual is diabetic, as well as height and weight. Following the initial attendance, each individual has a weight recorded by the group's consultant and uploaded to the Slimming World database for each subsequent week – measured at the start of each Slimming World class. Members can choose to forgo being weighed but the vast majority of members are weighed at each attendance they make.

4.2.1 Key Parameters for Retention

As with all datasets where data is recorded manually, there is potential for entry errors in the variables. To account for this, the data managers at Slimming World cleaned the data by setting what they believed to be plausible parameter values in Table 2. Values outside these parameters were excluded from the dataset.

Table 2: Data Retention Parameters

Variable	Minimum for Inclusion	Maximum for Inclusion
Age (years)	18	80
BMI (kg/m^2)	20	90
Height (cm)	135	210
Start Weight (lb)	80	600
3-Month Weight Change from Baseline (%)	-30	20
6-Month Weight Change from Baseline (%)	-40	30

12-Month Weight Change from Baseline (%)	-50	40
Pregnant	All Excluded	All Excluded
Breast Feeding	All Excluded	All Excluded
Target BMI (kg/m^2)	20	90

The lower and upper bounds for age are in place due to children not being the focus of the programme and older individuals often having conditions which can affect weight. BMI, height and weight restrictions are there as people who fall below the minimum parameter are unlikely to be Slimming World members as they do not need to lose weight. The upper bounds are because people above these are likely input errors. With the weight change, any change outside of these bounds is likely due to an input error or a medical condition as this weight change is extreme. For an example, if a member had to have a limb amputated, which resulted in a substantial loss of bodyweight. As well as these exclusions, target BMI values were excluded if an individual had a target BMI lower than 20kg/m^2 as Slimming World does not allow individuals who have BMI's at this level to set lower targets. Target BMIs that were higher than baseline BMI were also removed as these are likely to be input errors, and for those that aren't Slimming World is being evaluated as a weight loss programme and so these individuals are not relevant to the analysis.

4.2.2 The Variables in the Dataset

The baseline variables in the Slimming World dataset are displayed in Table 3. This table defines each of the variables that Slimming World collect in the first week of attendance for each individual. The baseline data includes demographics and diabetic status as well as their weight before the intervention has begun.

Table 3: Member Information at Baseline

Variable	Definition	Type of Variable	Unit of Measurement
ID	Member ID held my Slimming World used to link data	Discrete	Identifying code
Title	Prefix used in front of a person's name (Mr, Mrs etc.)	Categorical	Mr/Mrs/Miss/Ms/
Gender	The gender of the individual	Categorical	Male/Female/Other
Age at join date	The age of the individual at their first attendance	Continuous	Years
Height	The individual's self-reported height	Continuous	Cm
Weight	The weight of the individual measured at their first attendance and each week of attendance after	Continuous	KG
BMI	The BMI of the individual recorded each week using weight and height	Continuous	KG/m^2
Baseline date	The date on which the individual made their first attendance	Discrete	Date
Diabetic Status	Whether the individual has diabetes	Binary	Yes/no
Breastfeeding	Whether the individual was breastfeeding at the start membership	Binary	Yes/no
Pregnant	Whether the individual was pregnant at the start of their membership	Binary	Yes/no
Employment Status	Whether the individual was in full-time or part-time employment at the start of their membership	Categorical	Full-Time/Part-Time
Shift worker	Whether the individual is a shift worker	Binary	Yes/no
Has children living at home	Whether the individual had children living at home at the start of their membership	Binary	Yes/no
Is partner at home	Whether the individual was living with a partner at the start of their membership	Binary	Yes/no
Initial Target	The target weight that an individual sets as a goal	Continuous	KG
Join Type	The route of sign-up the individual took	Categorical	The category of join type
Income IMD quintile	The income IMD rank and score of the LSOA that the individual resides in	Continuous	Quintiles (1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th})
Education & skills IMD quintile	The education, skills and training IMD rank and score of the LSOA that the individual resides in	Continuous	Quintiles (1^{st}, 2^{nd}, 3^{rd}, 4^{th}, 5^{th})

After the first session, weekly values for weight and BMI are recorded. Slimming World also records how much the individual paid that session, whether the individual left the class early (after being weighed but before the IMAGE therapy), whether the individual was at their target weight (within 3lbs of target) and the group and consultant code of the attendance.

4.2.3 Missing Baseline Data

Whilst some data may be missing at random due to human or computer error, many of the fields are optional when filling out forms at Slimming World and there may be a reason why some individuals are more likely to complete forms than others. One hundred and five members had no recorded starting weight. Staff from Slimming World suggest this is likely to be individuals who attended IMAGE therapy without being weighed. These individuals were dropped as they represent a small proportion and without start weight they cannot be included in any meaningful analysis. Individuals with missing values for other variables remained in the dataset.

Table 4 sets out the missing data at baseline for key variables, for all those individuals who were involved in the final dataset for analysis.

Table 4: Member Key Variables Missing Summary

Variable	Missing	Percentage (%)
ID	0	0.0
Gender	0	0.0
Age at Join Date	0	0.0
Height (cm)	39,466	5.7
Start Weight (kg)	0	0.0
Start BMI (kg/m^2)	39,466	5.7
Diabetic Status	0	0.0
Employment Status[3]	440,624	63.6
Income IMD	183,019	26.4
Education, Skills and Training IMD	176,149	25.4
Has Children Living at Home	440,624	63.6

[3] Different consultants will likely have different approaches in the extent to which they encourage new members to fill out sign-up forms

Has a Partner Living at Home	440,624	63.6
Initial Target Weight (kg)	138,645	20.0
Initial Target BMI (kg/m^2)	169,741	24.5
Join Type	39,476	5.7

Whilst some variables had no missing values, not all variables held values for all members. Baseline BMI was not provided by Slimming World and so was calculated using the height and weight variables. Height was missing for 39,466 (5.7%) members as height records were only available for those who attended week 1. Therefore, BMI could only be calculated for those who attended the week 1 class. Join type was also recorded at week 1 rather than week 0 which means that values are missing for all new members that did not attend the second week of the programme.

IMD values for income and education and skills were found by converting members' postcodes at the Slimming World headquarters using the Ministry of Housing, Communities and Local Governments' (Ministry of Housing, Communities and Local Governments, 2015a) 'postcode lookup' tool which uses English Indices of Deprivation 2015 data. The Indices of Deprivation was the fifth release of statistics regarding deprivation with previous releases coming in 2010, 2007, 2004 and 2000 (Ministry of Housing, Communities and Local Governments, 2015b). Areas in the UK are split into LSOAs which generally have 1,000 to 3,000 people in each. Each LSOA has associated IMD values which the MHCLG uses to give individual postcodes IMD values (Office for National Statistics, 2019). A total of 176,184 (25.4%) members either did not have their postcodes recorded or did not have their postcodes matched to IMD scores – due to the fact that the MHCLG's postcode matching tool only converts English postcodes. For income IMD score, 6,712 (0.96%) individuals had values for deciles that were not integers and these values were set as missing rather than making assumptions about their true values. Because income IMD had a slightly larger proportion of missing values this was used to compare missing with non-missing for IMD. Those who did not have income IMD recorded were 0.77 years younger on average ($p<0.001$), and had a mean BMI 0.10kg/m^2 lower than those with income IMD recorded ($p<0.001$).

Income and education levels have been shown to be associated in society, with those with greater educational attainment often being able to demand higher incomes (Wiles, 1974). Due to this, the relationship between the variables for income IMD and education and skills IMD quintiles was investigated. The domain of income IMD included indicators based on the number of people that were in families that were deprived in regards to household income. These indicators included the number of people in families receiving financial support such as income support, jobseeker's allowance, and child tax credits. If a high number of individuals in the area fit into these categories, the area would receive a high deprivation score for income. The education and skills IMD domain included indicators regarding educational attainment in school for children in the area, and the number of adults with no or little qualifications or English language proficiency. This means whilst there is likely a relationship between the two, they are distinct which is why IMD uses both.

Whilst IMD is not perfectly representative of the levels of income and education for each individual, it does provide an indicator of the levels of deprivation for each measure in the local area. Because of this association, the correlation between the two variables was assessed. A correlation of 0.816 was found between the two variables when they were assumed to be continuous, which signifies a high correlation.

Slimming World members had the option of completing information on their employment, whether they have children living at home and whether they lived with a partner. It was clear a large proportion of participants did not complete this information (n=441,624; 63.6%).

Employment status and whether the new member lives with a partner and/or children were all collected via an optional employment form – which is why the missing data for all three is identical. Again, a comparison was made between baseline BMI and age for those that did and did not fill out the employment form. Those who did not fill out the form had a 0.33kg/m^2 higher BMI ($p<0.001$), and were 4.51 years older ($p<0.001$). With these baseline statistics both being significantly different it can be assumed that this data is not missing at random. This suggests that it could be those who are unemployed do not fill out the form or those that are without partners/children are less likely to fill out the form. The 'employment status' variable does not have an option for out of work so it is likely that those that do not fill out the form are without jobs.

However, it cannot be assumed that all those that have not filled out the form are unemployed.

The reason that those who are missing are older is likely because individuals that have retired, and therefore are no longer in the workforce, are generally older. The proportion of missing data for those who were 65 or older was 92.6% compared with 61.4% of those under 65. This significant difference ($p<0.001$) provides support to this hypothesis.

The final variable with a large proportion of missing data was the initial weight loss target that individuals set. There were 138,645 (20%) missing values for target weights which could either be because these individuals did not want to set a target; were not asked by their consultant to set a target; or the consultant did not record their target. Those that did not set a target had 1.1kg/m^2 higher BMI ($p<0.001$) and were 0.25 years older ($p<0.001$). These differences imply that the data may not be missing at random.

4.3 Describing the Population at Baseline

Table 5 describes the sample population at baseline. The mean age across all individuals in the dataset at baseline is 42.70 years. The mean weight in the cohort is 90.52kg which translates to a mean BMI of 33.31kg/m^2 – which comes under the classification of obese (NHS, 2016). Out of all members in the cohort, 2% were reported to be diabetic. For those who filled out the employment form, 31% were in full-time work - with the other 69% being in part-time work; 58% lived with at least one child; and 74% lived with a partner.

IMD was converted from deciles into quintiles (0, 1, 2, 3, 4). The mean scores for income and education and skills IMD were 2.01 and 1.84 respectively. Slimming World members initially target a mean BMI of 28.04kg/m^2.

Table 5: Summary of Baseline Variables

Variable Label	n	Mean	SD	Min	Max
Age at Join Date (years)	692,945	42.70	13.58	18	80
Height (cm) (week1)	653,479	164.75	7.54	135	210

Start weight (kg)	692,945	90.52	19.52	44.68	277.14
Start BMI (kg/m^2)	653,479	33.31	6.53	20.00	89.53
Diabetic Status (0=not diabetic, 1=diabetic)	692,945	0.02	0.15	0	1
Employment Status (0=part-time, 1=full-time)	252,321	0.31	0.46	0	1
Income IMD Quintile (1-5)	509,926	3.01	1.37	1	5
Education, skills and training IMD Quintile (1-5)	516,796	2.84	1.36	1	5
Has Children Living at Home (0=no, 1=yes)	252,321	0.58	0.49	0	1
Has Partner Living at Home (0=no, 1=yes)	252,321	0.74	0.44	0	1
Initial Target Weight (kg)	557,613	76.13	16.58	0	245.85
Initial Target BMI (kg/m^2)	523,204	28.04	5.58	20.00	84.68
Initial Target Weight Loss (kg)	557,613	-13.77	9.89	-161.48	0
Initial Target BMI Loss (kg/m^2)	523,204	-5.05	3.56	-55.76	0

Table 6 shows the proportion of males and females in the sample, with the majority (95.4%) being female.

Table 6: Summary of Gender

Gender	n	%
Females	660,868	95.4
Males	32,077	4.6

Figure 5: Distribution of Baseline BMI

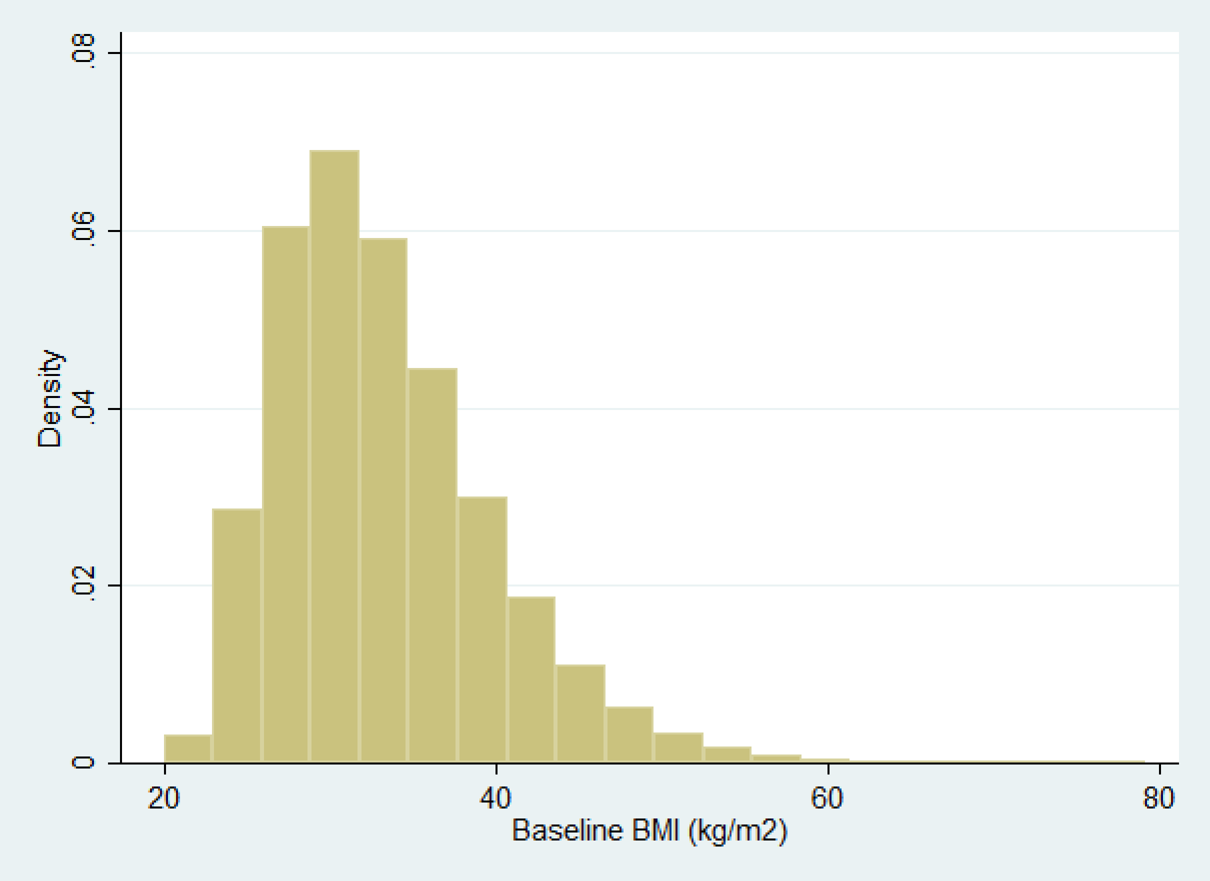


Figure 5 shows the distribution of BMIs in the Slimming World sample under 80kg/m^2, as only a small proportion of the sample had BMIs of 80kg/m^2 or above. The distribution shows a positive skew with a value of 1.05. This is likely to be present due to very few people having BMIs of 50-plus, and selection bias in that those who would be on the lower tail of a BMI distribution not joining the Slimming World programme as they do not need to lose weight. A summary of the distribution of baseline BMI by BMI classifications is shown below in Table 7, where obese I represents those with BMIs between 30kg/m^2 and 35kg/m^2, obese II represents those with a BMI between 35kg/m^2 and 40kg/m^2 and obese III represents those with a BMI of 40kg/m^2 or higher. The most common group of members are those that are obese I with the least common being healthy weight – most likely because the majority of people in this BMI classification from the full population do not feel they need the assistance of a weight management programme.

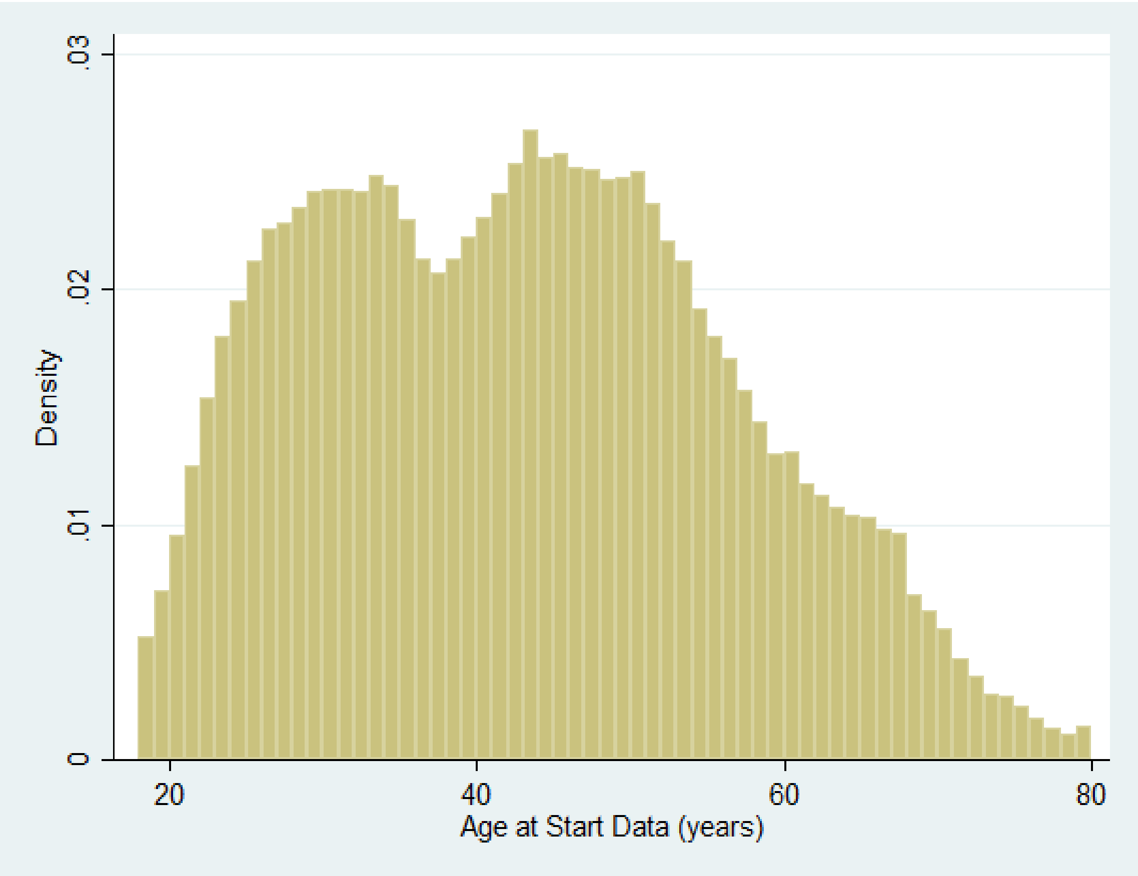
Table 7: Distribution of Members by BMI Classification at Baseline

Baseline BMI Classification	Baseline BMI (kg/m^2)	N	N (%)
Healthy Weight	18.5-24.99	36,153	5.5
Overweight	25-29.99	194,317	29.7
Obese I	30-34.99	202,727	31.0
Obese II	35-39.99	124,624	19.1
Obese III	40+	95,658	14.6

*BMI Classifications from NICE (2014)

Members' age at the date they join Slimming World is characterised by a bi-modal distribution as seen in Figure 6. This shows that the age of members peaks at around 30 and then again in people's mid-40s.

Figure 6: Distribution of Age at Start Date



A summary of the distribution by age group is shown in

Table 8. The most common group is members in their 40s followed by those in their 30s and then 20s. The least populated group is those that are 60 or older.

Table 8: Distribution of Members by Age Group at Baseline

Age Group	N	N (%)
18-29	139,911	20.2
30-39	159,816	23.1
40-49	173,524	25.0
50-59	131,266	18.9
60+	88,428	12.8

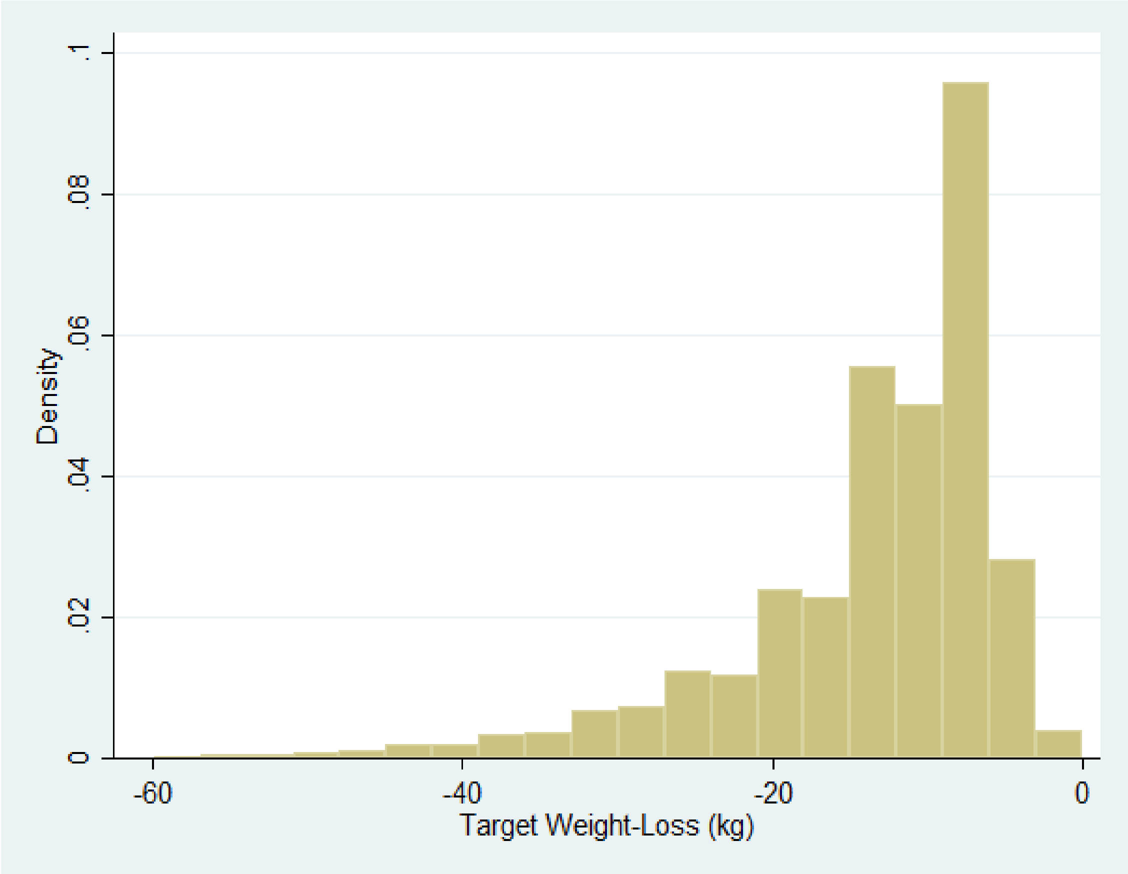
Table 9, below, shows the distribution of both income and education and skills IMD. It can be seen that for income IMD, each group is well represented in the Slimming World sample, with all groups representing at between 18% and 22% of the sample. For education and skills IMD participants each group is still reasonably well represented, but there are fewer participants from the least deprived areas in terms of education and skills, with under 15% of the full sample being from these areas. The three best represented groups for education and skills IMD are the three most deprived groups.

Table 9: Proportion of Individuals in each IMD Quintile

Quintile	Income IMD (%)	Education and Skills IMD (%)
1	18.1	21.5
2	20.6	22.2
3	21.5	21.7
4	21.5	19.7
5	18.3	14.9

Figure 7, below, shows the distribution of weight-loss targets up to 60kg, as the frequency of weight-loss targets of 60kg or more was small. The histogram shows that few people aim to lose less than 5kg, with most aiming to lose 5-15kg of their starting weight. The frequency of weight-loss targets decreases with the size of the target.

Figure 7: Distribution of the Target Weight-Loss set by Slimming World Members



Appendix 3 and Figure 8 show the join type of all new members in the 2014 cohort. Four of these join types were explained in section 4.1, with the additional category being re-join. Re-join is classified as an individual who had previously been a member of the programme and re-joined as a new member in 2014. It is possible to identify individuals who re-join if the data manager at Slimming World was able to match them to their original member ID.

The data shows that almost half of individuals signed up to the programme on the standard tariff with no type of discount. Just under 10% signed up at the Slimming World class with a Countdown pre-paid package. Around one in five signed up with discounts found in magazines. Only a small percentage of new members joined through SWoR (2.7%). Over 1 in 5 of new members in 2014 had been members prior to 2014.

Figure 8: Distribution of Join Types

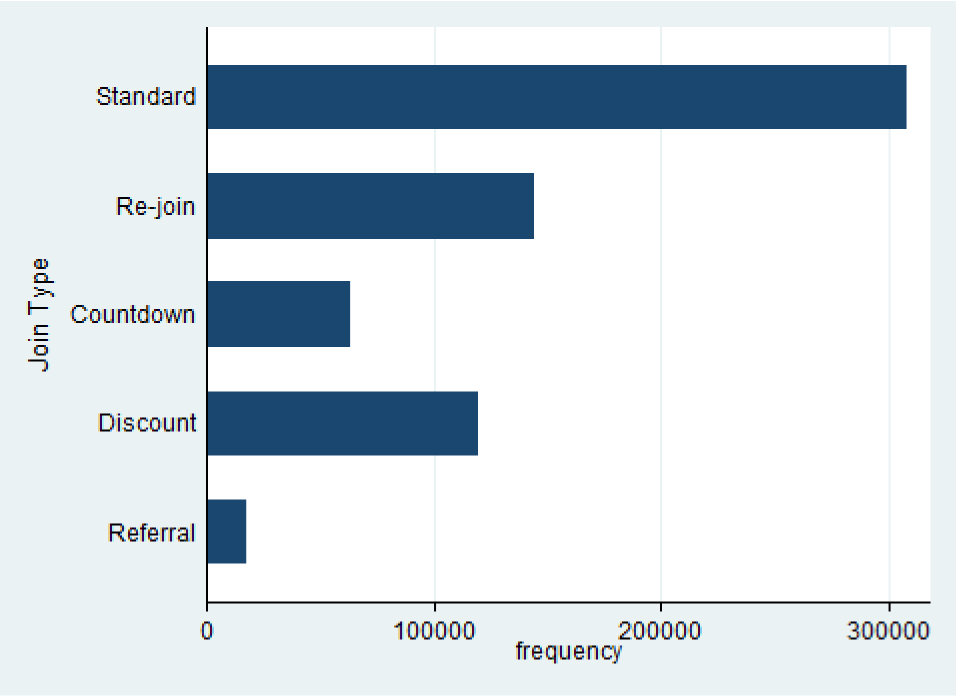


Table 10: Baseline Summary by Join Type

Join Type	Age	Baseline weight (kg)	Baseline BMI (kg/m^2)	Income IMD quintile	Education IMD quintile	Target Weight Loss (kg)
Standard	41.84	89.69	32.96	2.03	1.84	-14.11
Re-join	43.68	90.20	33.22	2.06	1.93	-12.16
Countdown	45.33	91.20	33.44	2.36	2.18	-13.93
Discount	41.54	91.12	33.63	1.77	1.61	-13.62
Referral	47.28	101.38	37.22	1.77	1.63	-17.06

Table 10 shows key baseline statistics of the members in the dataset by join type. Those that joined the Slimming World programme via the referral scheme tended to be older, have a higher BMI, and set higher targets for weight loss than those who had joined via a standard membership, those that had re-joined the programme, those who purchased a countdown package and those who joined the programme using a discount voucher. Those in the discount and referral groups lived in the most deprived areas in terms of both income and education on average, with those that joined Slimming World via a countdown membership being more likely to be from the least deprived areas.

Table 11: Summary Statistics by Income IMD Quintile

Income IMD Quintile	Age	Baseline Weight (kg)	Baseline BMI (kg/m^2)	Target Weight Loss (kg/m^2)
0	39.89	93.49	34.55	-14.94
1	41.58	92.05	33.84	-14.40
2	43.06	90.87	33.32	-13.90
3	44.44	89.51	32.77	-13.37
4	45.41	88.30	32.24	-12.92

When reviewing the differences in age, baseline weight and BMI, and target weight loss, a clear pattern emerges in Table 11. Those living in less income deprived areas, tend to be older, have lower baseline weights and BMIs, and set less ambitious targets in terms of weight loss. A similar pattern is present when reviewing education and skills IMD quintiles.

Table 12: Join Type Proportions for each Income IMD Quintile

Income IMD Quintile	Standard (%)	Re-join (%)	Countdown (%)	Discount (%)	Referral (%)
1	47.4	18.0	6.8	23.0	4.8
2	48.1	18.6	9.4	19.9	3.9
3	49.1	18.8	11.3	17.2	3.6
4	49.1	19.2	13.0	15.5	3.3
5	48.3	19.9	15.2	13.8	2.8

Again, clear patterns emerge in Table 12 with join types between with income IMD quintiles. Less income deprived Slimming World members are significantly more likely to join Slimming World via a countdown membership, while those in more deprived areas are more likely to join Slimming World using a discount voucher or via a GP referral. Again, a similar pattern was seen across the education and skills IMD quintiles.

Now the Slimming World case study has been described at baseline, the next section will review the outcome data in the dataset: attendances and weight change.

4.4 Outcome Data

The outcome variables in the dataset provided by Slimming World are recorded in the weekly attendance data. This includes the weight, BMI and attendance patterns for each individual. Additional variables, shown in Table 13, were created with the purpose of better assessing the Slimming World programme based on both the theoretical framework in Chapter 3, for the purpose of analysis, and NICE (2014) recommendations, to illustrate how effective the programme is against NICE objectives. Using variables such as total attendances in the first 12 weeks, and LOCF weight change at 3 months, initial engagement can be summarised and used as outcome variables in regression analysis. The targets set by individuals and whether they achieve them can also be used to assess programme effectiveness from the point-of-view of members.

Table 13: Outcome Variables

Variable	Definition	Type of Variable	Unit of Measurement
Total attendances	The total number of attendances the individual makes over the 24-month period	Continuous	Attendances
Total attendances at 12 weeks	The total attendances the individual makes in the first 12 weeks	Continuous	Attendances
Attendance at 3-6, 6-12, 12-24 months	Whether the individual made at least one attendance in each time-period	Binary	Yes/no
Completer	Whether the individual attended at least 10 of the first 12 weeks of the programme	Binary	Yes/no
LOCF weight at 3/6/12/24 months	LOCF weight of the individual at the specific time-point	Continuous	Kgs
LOCF weight change at 3/6/12/24 months	The weight change between baseline and the last observed weight at each time-point	Continuous	Kgs
3/5/10% weight change	Whether the individual achieves each percentage of weight loss during their time in the Slimming World programme	Binary	Yes/no
LOCF BMI at 3/6/12/24 months	The LOCF BMI of the individual at the specific time-point	Continuous	Kg/m^2
LOCF BMI change at 3/6/12/24 months	The BMI change (unit and %) between baseline and the last observed weight at each time-point	Continuous	Kg/m^2, %
Target BMI loss	The BMI points and % of baseline BMI the individual would have to lose to reach their target BMI	Continuous	Kg/m^2, %
Target reached	Whether the individual was at or below their target weight at their final attendance	Binary	Yes/no
BMI change to healthy	The BMI change required for the individual to have a healthy BMI (BMI of 25kg/m^2)	Continuous	Kg/m^2
Healthy BMI reached	Whether the individual's LOCF BMI was 25kg/m^2 or lower	Binary	Yes/no
Left Early attendances in first 12 weeks	The percentage of attendances in the first 12 weeks	Continuous	%

4.4.1 Unobserved Attendance Data

As well as missing baseline data, there was missing data in subsequent weeks of the programme as not all those who join the Slimming World programme attend every session. For example, 39,466 of the 692,945 individuals who joined in 2014 did not attend the week after the week they joined the programme. This means there is missing data for these individuals as Slimming World cannot record data without attendance.

As the reason for an individual leaving the programme, and what happens to each individual's weight when they stop attending, is unknown assumptions have to be about weight trajectories over time and this will be discussed in later chapters. For the purpose of describing the outcomes, at 3 months, LOCF weight-change is used as the outcome of interest as the initial Slimming World programme, both countdown and referral, is determined as 12-weeks. At 6, 12 and 24 months, LOCF weight change is used for outcomes but only for those who have continued attending Slimming World classes past 3, 6 and 12 months. This is because if the last observation was recorded a long time prior, it is a strong assumption to make that the individual's weight remains constant.

4.2.2 Attendance

Appendix 4 shows the proportion of individuals that stay in the programme for various lengths of time. Of the 692,945 that joined Slimming World in 2014, 44.15% made at least one attendance at any point after the initial 12 weeks. Nearly a quarter of individuals made at least one attendance after the first 6 months and just under an eighth of individuals made an attendance over a year after joining the programme. This is illustrated in Figure 9 below.

Figure 9: Number of Members that Remain in the Programme through each Time-Period

Individuals continuing to attend classes after the initial 12-week period means that when evaluating long-term results, the dataset still holds data for 81,910 individuals still attending after the first year. For the other 611,140 individuals that joined in 2014, long-term weight change will have to be predicted. Outcomes at 6, 12 and 24 months will only be reviewed for those who continue attending the programme.

Figure 10: Distribution of Attendances in the First 12 Weeks

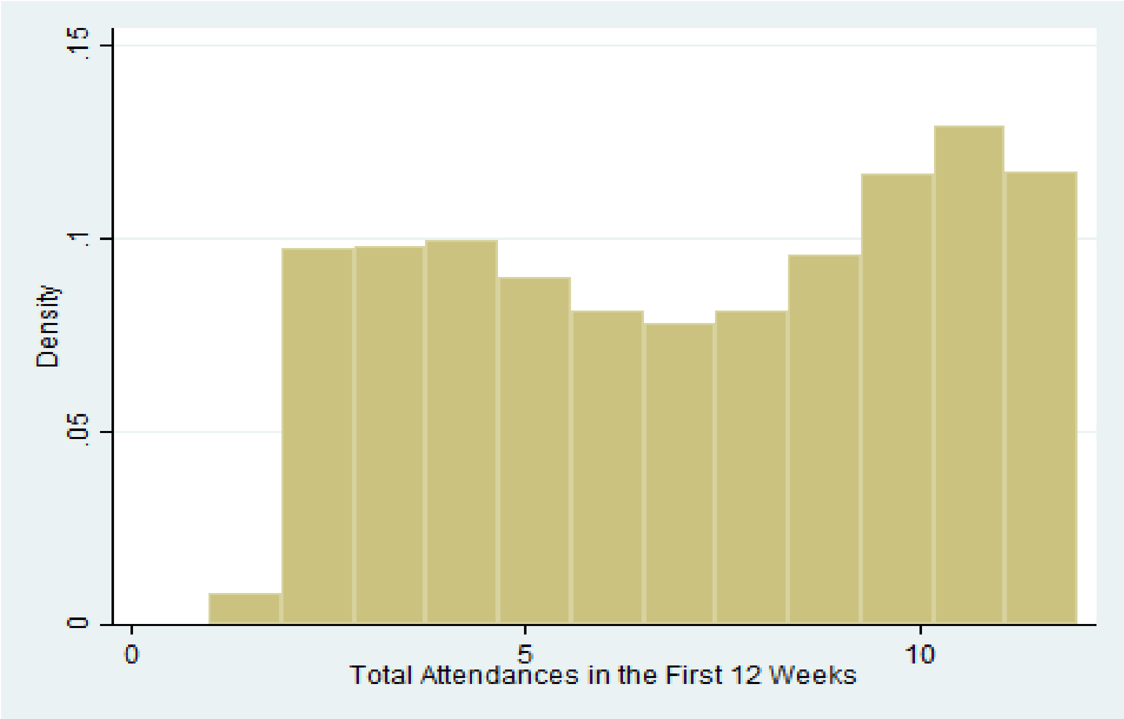


Figure 10 shows the distribution of what proportion of individuals attend each number of sessions in the first 12 weeks, which has a skewness of -0.11. The completion rate for the initial 12-week programme across the entire sample was 33.2%. The least common number of attendances is 1 which is unusual as it significantly less common than all other values (all p<0.001).

4.2.3 Clinical Outcomes

Table 14 shows the proportion of members that achieved clinical outcomes set out by NICE (2014) and the literature (Wing et al., 2011). Almost half of all members meet the goal of 3% weight change whilst nearly two-thirds of those that joined via SWoR achieved it. Almost 1 in 8 members achieve a weight loss of 10%; this rises to more than 1 in 5 for those who entered the programme by way of SWoR. All differences are significant between the whole sample and the referral group with p-values of <0.001. Members who join through SWoR are significantly less likely to reach a healthy BMI than all other groups, but this is likely due to individuals joining Slimming World via SWoR being further from a healthy BMI at baseline – shown in Table 10.

Table 14: Proportion of Members that Achieve Weight Change Levels

Members	N	Achieved 3% Weight Change (%)	Achieved 5% Weight Change (%)	Achieved 10% Weight Change (%)	Achieved Healthy BMI (%)
All	692,945	48.7	31.4	11.8	11.4
Standard	307,465	54.8	36.9	14.3	13.5
Re-Join	144,447	27.00	12.4	2.5	8.3
Countdown	63,875	58.6	39.3	15.1	11.4
Discount	119,786	47.3	29.7	10.9	10.4
Referral	17,896	63.1	46.7	21.1	2.2

4.2.4 Weight Outcomes

After the initial 12-week period in the Slimming World programme, the mean LOCF weight-change across all sample members was -3.20kg, with the distribution of weight-change between -20kg and 10kg being shown in Table 15 below. A skew is present with the majority of participants experiencing a small weight-loss inside the Slimming World programme.

Table 15: A Histogram of Weight-Change at 12-Weeks

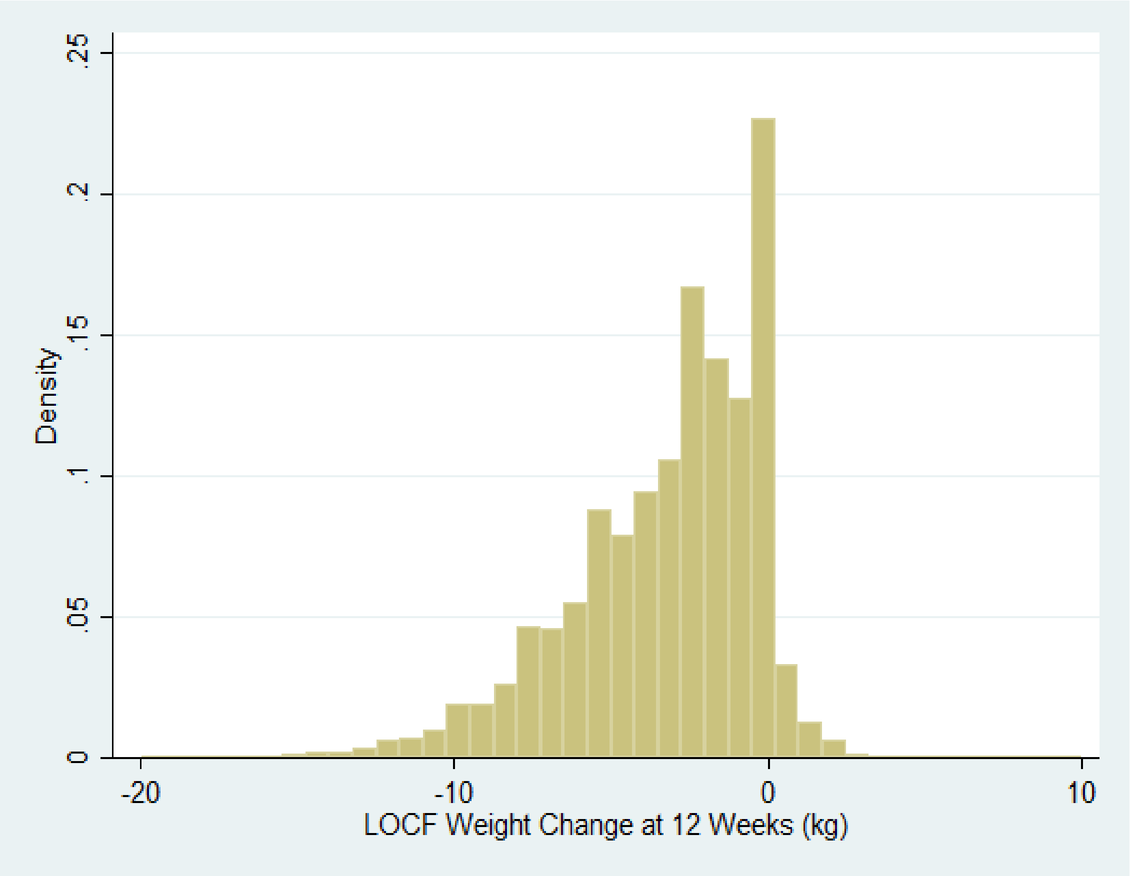


Table 16 shows the outcomes of the individuals that remained in the programme after 3, 6 and 12 months.

Table 16: Outcomes by Time-Period of Leaving the Programme

Time Period (Months)	N	Total Attendances	LOCF Weight Change 3 Months (kg)	LOCF Weight Change 6 Months (kg/m^2)	LOCF Weight Change 12 Months (kg/m^2)	LOCF Weight Change 24 Months (kg/m^2)	Target Reached (%)	BMI at last Attendance (kg/m^2)
≤3	383,064	5.05	-3.20	-	-	-	1.9	32.36
3-6	142,303	13.79	-4.11	-4.46	-	-	10.0	31.68
6-12	85,676	26.97	-5.25	-7.11	-6.92	-	20.5	31.22
>12	81,902	61.50	-6.11	-9.62	-11.36	-10.48	32.5	30.35

Table 16 shows that those who remain in the programme for longer have a greater weight-loss than all other groups over the initial 3 month period (all $p<0.001$). Also of interest is that at 12 months, those that leave the programme between 6 and 12 months weigh more than they did at 6 months. For those that leave the programme in the 6 to 12 month period, the mean weight at 6 months is lower than the LOCF weight at 12 months. For those who stay in the programme for longer than 12 months, the mean weight loss is less at 24 months than 12 months.

Table 17: Outcomes by Join Type

Join Type	N	Total Attendances in First 12 Weeks	Total Number of Attendances	LOCF Weight Change 3 Months (kg)	Target Reached (%)
Standard	307,465	7.47	17.17	-3.63	11.0
Re-join	114,447	6.21	10.73	-1.76	3.6
Countdown	63,875	8.44	21.04	-3.82	11.6
Discount	19,786	7.49	16.42	-3.20	9.6
Referral	17,896	9.06	24.12	-4.65	16.3

There are distinct patterns between the outcomes of the five different entry routes into Slimming World shown in Table 17. The members that join Slimming World through SWoR attend significantly more regularly than all other groups during the initial 12-weeks and have more attendances in total (all $p<0.001$). Those that re-joined the programme attended less sessions than all other groups and lost less weight. Referral members lose the most weight, while those that join via countdown memberships are the most likely to reach their target weight.

Table 18: Outcomes by Age Group

Age Group	N	12-Week Attendances	Total Attendances	LOCF Weight Change 3 Months (kg)	Target Reached (%)
18-29	139,911	6.70	12.74	-2.93	7.0
30-39	159,816	6.93	14.16	-3.12	8.2
40-49	173,524	7.25	16.10	-3.31	9.8
50-59	131,266	7.51	18.17	-3.33	11.7
60+	88,428	8.05	22.86	-3.35	15.6

Strong patterns emerge when looking at attendance outcomes by age group in Table 18. Older groups attend more sessions, both in the first 12 weeks and 24-months on average. However, weight-loss stayed relatively constant between the age groups, with all groups losing between 2.93 and 3.35kg on average. Despite this, older age groups are significantly more likely to reach their target weight in the Slimming World programme.

Table 19 shows the outcomes by the various clinically defined BMI groups. The data shows that those who have higher BMIs attend more sessions than those who with lower BMI, lose more BMI points on average and are less likely to reach their target in the 24-month follow-up period; this is likely due to those in higher BMI groups setting larger targets as they have a larger amount of excess weight. A further explanation could be that it takes longer to lose a greater amount of weight.

Table 19: Outcomes by BMI Group

Baseline BMI Classification	Baseline BMI (kg/m^2)	N	12-Week Attendances	Total Attendances	LOCF 3 Month Weight Loss (kg)	Target Reached (%)
Healthy Weight	18.5-24.99	36,153	6.55	11.47	-1.95	9.3
Overweight	25-29.99	194,317	7.21	14.71	-2.63	9.0
Obese I	30-34.99	202,727	7.41	16.48	-3.16	9.0
Obese II	35-39.99	124,624	7.47	17.50	-3.62	10.1
Obese III	40+	95,658	7.53	18.57	-4.25	12.3

When members attend classes, they have a choice of whether to stay for IMAGE therapy and participate in a discussion about behavioural change with other members and the consultant, or leave before this. As not all individuals are consistent with whether they leave the classes they attend early or not, a method for summarising how often the individual leaves early was created. First, it has been assumed that all individuals stay for their first class as there is no data on whether or not they leave early for the initial attendance. It is likely that the individuals do stay for their first full class as this is when they are provided with all the information about how the programme works. To identify the effect of leaving early, completers of the programme are compared. This is so only individuals who attend regularly are included in the comparison. These are sorted into four groups shown in Table 20.

Table 20: Outcome Comparison of Completers with Various Leave Early Rates

Early Leaver	N	12-Week Attendances	Total Attendances	LOCF BMI 3 Months (kg)	Target Reached (%)
Leave early <0.25	136,682	11.04	36.90	-5.85	23.3
Leave early <0.5 & =>0.25	48,965	11.00	29.01	-5.34	18.9
Leave early=>0.5 & <0.75	34,615	10.83	24.46	-5.03	16.1
Leave early =>0.75	9,867	11.05	25.36	-5.09	17.7

Table 20 shows that those who leave early in less than 25% of sessions in the first 12-weeks perform significantly better than all other groups in the first 12 weeks which means that even though those that leave early are attending and being weighed, they do not receive the benefit of the IMAGE therapy which is shown by the lesser weight loss.

Table 21 shows outcomes by income IMD group. A trend appears with those who are in less deprived areas making more attendances and losing more weight between quintiles 1 and 4, with those in quintile 5 attending less and losing less weight than those in quintile 4. However, those in quintile 5 are more likely to reach the target weight they set when joining the Slimming World programme.

Table 21: Outcomes by Income IMD Quintile

Income IMD Quintile	N	12-Week Attendances	Total Attendances	LOCF Weight Change 3 Month (kg)	Target Reached (%)
1	92,140	7.22	16.14	-3.27	9.5
2	104,959	7.32	16.80	-3.31	10.0
3	109,826	7.41	17.34	-3.33	10.6
4	109,706	7.46	17.61	-3.34	10.9
5	93,295	7.42	17.40	-3.28	10.7

When reviewing the relationship between education and skills IMD quintiles in Table 22, a less strong relationship between deprivation and lower attendances and less weight loss is less apparent. Those in the middle quintile attend the most classes with those in the most and least deprived quintiles attending the least Slimming World classes. In regards to weight change, those in the less deprived quintiles lose less weight, but are more likely to reach their target weight – because of the lower starting weight and more conservative targets set by those in less deprived groups.

Table 22: Outcomes by Education & Skills IMD Quintile

Education & Skills IMD Quintile	N	12-Week Attendances	Total Attendances	LOCF Weight Change 12-Week (kg)	Target Reached (%)
1	111,209	7.29	16.60	-3.34	9.9
2	114,543	7.38	17.14	-3.34	10.3
3	112,057	7.43	17.41	-3.35	10.7
4	101,988	7.42	17.36	-3.30	10.7
5	76,999	7.31	16.80	-3.17	10.4

4.5 Summary

This chapter has set out the key features of the Slimming World programme and the dataset of Slimming World members that will be used as a case study. This chapter included a description of the sample of Slimming World members and some key outcomes by different subgroups. The key findings in this chapter are listed below:

- The sample of individuals in the Slimming World dataset represent a diverse sample in terms of characteristics
- Around 44% of participants who join Slimming World continue attending after the initial 12-week period
- Participants who join the programme via Slimming World on Referral lose more weight than any other join type
- Individuals that are more obese attend more classes and lose more weight on average
- Income and education deprivation had no meaningful effect on weight-loss at 12-weeks

The dataset features a number of strengths that will make the analysis performed a valuable addition to the current literature. The first strength is the size of the dataset. With almost 700,000 individuals in the sample the case study represents one of the largest studies on weight management that has been performed. As well as this, Slimming World routinely collect a large amount of data on all members, and a large number of participants have full data available at baseline. Another positive of the dataset is that over 80,000 individuals have data for over one year with some individuals having up to 2-years of follow-up data.

A limitation of the dataset is that the analysis is limited to data routinely collected by Slimming World. Because the data was not collected for the purpose of this research, not all individual characteristics that can affect weight management are included, and so proxy variables have to be used, which may be less effective. As well as this, as not all fields in the sign-up forms are mandatory, there is a substantial amount of missing data for some variables. The final limitation is that weights cannot be collected for individuals who stop attending Slimming World and so weight trajectories for those outside the programme are unknown.

The next chapter will go on to discuss what variables can be used as proxies to test the theoretical framework and the regression methods that will be employed. Whilst some patterns have emerged from reviewing outcomes in the descriptives, the regression analysis in the next chapter will be able to test whether this is correlation or causation, and predictions will be able to be formed about what happens to different individuals using these characteristics.

Chapter 5: Analysis of Weight-Change and Attendance in the Slimming World Dataset

The theoretical framework of weight management in Chapter 3 provided an overview of factors that influence weight management behaviour, including the individual characteristics and demographics that might predict greater success with weight loss and weight loss maintenance.

The first objective of this chapter is to test the hypotheses made by these theories of weight management in order to identify the key influencers of weight change in a weight management intervention. Data on the Slimming World programme will be used as a case study to test these hypotheses and identify predictors of weight-change and attendance.

Following this, the identified variables will be used to make predictions of the probability of individuals continuing to attend the Slimming World programme, and weight-change. Predictions of weight-change will then be made using the Heckman-correction for those who continue attending the programme, and those who leave the programme, and are therefore unobserved in the Slimming World data. These predictions of weight-change within the Slimming World programme will be used to inform the initial 24-months of cost-effectiveness analysis, which is defined in the model as the weight-loss period.

If key factors that predict weight-change in behavioural weight-management programmes can be identified from the analysis, then factors can be used to inform longer term modelling and make more accurate predictions of long-term weight-trajectories. By improving the accuracy of long-term weight-trajectories, modelling would better represent real-world outcomes, and therefore improve estimates of cost-effectiveness.

5.1 Empirical Specification

Whilst the Slimming World data is rich in terms of the number of variables available, and the number of individuals that are in the programme, because the data was not collected for the purpose of this specific research there are limits on the analysis and tests that can be performed. Whilst some explanatory variables from the theoretical framework are available in the data, not every variable from the theoretical framework has been collected and so proxy variables must be used. This section will first set out which variables have been found to be the most appropriate in the Slimming World dataset.

Following this, the empirical specifications for each theme (rational choice, time-preference and habits and self-control) will be presented using the proxy variables, and will be combined into one overall equation to assess the theoretical framework and make predictions about weight change. The frameworks in each theme will be tested by identifying the effect magnitudes for each independent variable that have been input into a regression model as a proxy for a theory on weight management. These relationships between the explanatory variables and weight change will then be used to form predictions about weight change based on individual characteristics, which will be used in cost-effectiveness modelling.

5.1.1 Rational Choice

Six variables were included in the rational choice framework to explain weight change (ΔW_i), shown in Equation 15 below. These were how far the individual is from their ideal weight ($W_i - W_{Ii}$), their budget constraint (I_i), how many free hours they have per week (T_i), how supportive the individual's partner is (PS_i), how much discrimination the individual receives (B_i) and how knowledgeable (K_i) the individual is about obesity and weight management. Whilst some directly correspond with the variables available in the dataset, for others, proxy variables were considered. These are described below.

Equation 15

$$\Delta W_i = \mathrm{f}((W_i - W_{Ii}), I_i, T_i, PS_i, B_i, K_i)$$

The first variable in the rational choice theoretical framework created in Chapter 3 was how overweight the individual is compared with their ideal weight (Ruhm, 2012; Dragone and Savorelli, 2012; Rosin, 2012). There were two potential methods of building this variable using the variables available in the Slimming World dataset. The first was that it could be assumed that every individual has a homogenous ideal weight (or BMI to control for height) that is set by society (or clinicians – a BMI under 25), and those that are furthest above this have the largest utility loss from their weight, with each extra pound of body weight reducing utility by more than the last (Lakdawalla and Phillipson, 2009). However, it is unlikely that every person has the same image of their ideal body, and some may maximise their utility from their bodyweight at different levels than others (Oswald and Powdthavee, 2007; Anand and Gray, 2009). Instead, the assumption was made that the target BMI/weight set by an individual at their registration for the Slimming World programme is their own personal ideal weight that they would gain the most utility from. In this case the difference between the individual's target weight and their weight yields their utility loss. A limitation of this assumption is that it is likely that people who are very obese set targets that are interims, which are made with the intention of being a realistic target rather than being a final target which would be their ideal weight, although recent study showed that setting an ambitious target improved weight loss (Avery et al., 2016). Equation 16 illustrates the rational choice econometric model. The first explanatory variable is measured by the difference between the individual's weight at baseline ($W_{0,i}$) and the individual's personal ideal weight ($W_{x,i}$) (Ruhm, 2012). Target weight was chosen over a healthy weight (defined by a BMI of 25kg/m^2 or lower) as a target weight incorporates preferences and therefore the bodyweight that individuals derive most utility from.

Equation 16

$$\Delta W_i = \beta_0 + \beta_1\left(W_{0,i} - W_{x,i}\right) + \beta_2 I_i + \beta_3 P_i + \beta_4 C_i + \beta_4 J_i + \beta_5\left(BMI_{B,i} - 25\right) + \beta_6 R_i + \beta_7 D_i + \beta_8 (A_i * E_i) + \varepsilon_i$$

For the variable of disposable income, the income IMD quintile ($\boldsymbol{I_i}$) of the area that each individual lives in has been chosen (Drewnowski and Darmon, 2005). A problem with this proxy is that in each LSOA there were on average 1,614 people, and it is limiting to assume that each of these people have identical budget constraints (Stokes, 2012). Seward (2014) highlights that income affects desire to lose weight with those in low-income groups having a lower desire to lose weight and fewer weight loss attempts. However, if an individual became a Slimming World member then the assumption can be made that the individual has signaled they were attempting to lose weight.

The next variable that required a proxy to be found was the amount of free time individuals have (Cawley, 2004). It was assumed that those in full-time work, rather than part-time work, will have less free time, as those in full-time work must allocate more hours to work. Another proxy for the amount of time a person has available was whether the individual has a partner or children at home as both of these come with responsibilities that could take time out of a person's day. Making this assumption was limiting as there will be some people who cook healthy meals because they want their children to eat well, or exercise because it is an activity they do with their partner. Another problem with this proxy was missing data. Slimming World collected data regarding whether the individual is employed, has a partner and has children, in an optional additional form. As the form is optional, there was a large amount of missing data for the employment, partner and children variables. However, initially, the proxy for time constraint are whether the individual is in full-time or part-time work (J_i) and whether the individual has a partner (P_i) and/or children living at home (C_i).

As the level of spousal support each individual receives is not stored in the data, a proxy would have be needed to test this theory (O'Neil et al., 2015). However, whilst the Slimming World dataset has information about whether each member has a partner, there is no way to tell the difference between supportive and non-supportive partners and so due to uncertainty about any proxy, this variable was not included.

The next variable that was hypothesised to influence weight change was the amount of discrimination each individual receives as a result of their weight (Dragone and Savorelli, 2012). If much of discrimination comes in the workplace, such as a lack of promotion or a wage penalty, it could be that those in full-time work are discriminated against the most and therefore have the largest utility loss (Brown and Routon, 2018) However, it could be that those who only have part-time employment are discriminated against so heavily that they cannot gain entry to the full-time job market (Flint et al., 2016). In this case, these individuals would have the most incentive to improve their weight management. It is likely that those that have the most excess weight are likely to receive the most discrimination, so the difference between baseline BMI and a healthy BMI (25kg/m^2) was the most appropriate proxy to use to test this hypothesis.

The next variable in the rational choice framework was how much knowledge an individual has about the risks of obesity and losing and maintaining weight, which is unknown (Grunert, 2012). It may be that Slimming World members that have joined through SWoR (R_i) are at an advantage as they have gained knowledge about the risks of obesity from their GP. Similarly, individuals that have had a health shock, which in the Slimming World database could be those with type 2 diabetes (D_i) may have also gained additional knowledge about the effects of their risky behaviour from doctors and other medical staff (Etile, 2000). With improved knowledge about the risks, these individuals may be more equipped to manage their weight successfully, as well as being likely to have more motivation to manage their weight as they are more aware of the consequences.

Education could also have an impact on knowledge as those that are most educated may be able to better process their doctor’s information (Grossman, 1972). Those who attended the most Slimming World classes are also likely to have taken in the most information as they have had the most exposure to the programme. As well as having data on whether the individual attended the session or not, there is data recorded on whether the individual left before the IMAGE therapy, and therefore did not receive the full extent of the intervention that week. It can be assumed that as the goal of IMAGE therapy is to provide information and support those that attend and stay for the most sessions should be better equipped to lose weight in the Slimming World programme and maintain their weight loss. Again, this should be coupled with education as the more educated are likely to process the IMAGE therapy more effectively. However, it is likely that the individuals that attend more sessions are also more motivated and engaged with the programme so this selection bias should be taken into account. The final variable in Equation 16 was an interaction between the information the individual receives from attendances where the individual stayed for the full session ($\mathrm{A_i}$), and the education IMD score (E_i) as individuals who are better educated are more likely to process new information more efficiently (Etile, 2000; Grunert et al., 2012).

Appendix 5 shows a summary of the each of the theories involved in the rational choice framework, the ‘ideal’ variable that would have been the most appropriate variable to test the hypotheses, and the proxy variable that was able to be used.

5.1.2 Time-Preference

In the time-preference framework, shown in Equation 17, the 3 variables included were the individual’s discount rate (D_i), their probability of a health shock (H_i), and whether the individual is a hyperbolic or exponential discounter (HD_i). Again, some variables in the time-preference framework do not correspond directly with those available in the Slimming World dataset and so proxy variables were used .

Equation 17

$$\Delta W_i = \mathrm{f}(D_i, H_i, HD_i)$$

A proxy for discount rate was needed as the discount rate for each individual in the programme was unknown (Richards and Hamilton, 2012). One proxy for discount rate was an individual’s educational attainment. This is because those who have stayed in education for a longer time are likely to either be more patient, as those that continue with education delay the reward of wages for higher future wages, or have learned how to be more patient through their education (Van der Pol, 2011; Fersterer and Winter-Ebmer, 2003; Perez-Arce, 2017). This is also shown by the relationship between education and BMI (Atella and Kopinska, 2014). Ideally, the educational attainment level that each individual has reached would be used, but Slimming World does not ask for this from members and so proxies were required. Education IMD quintile was used to make assumptions regarding the educational attainment of individuals in the area. Here it must was assumed that each individual had the average education level in the area which is limiting but unavoidable. Therefore the first variable in the time-preference empirical framework, shown in Equation 18, was education IMD quintile (E_i).

Equation 18

$$\Delta W_i = \beta_0 + \beta_1 E_i + \beta_2 D_i + BMI_{B,i} + \beta_3 a_i + \varepsilon_i$$

Both whether the individual is diabetic, and BMI at baseline were included as proxies for the probability of a health shock in the next period. (Richards and Hamilton, 2012). However, the question is whether all diabetics report to Slimming World that they have type 2 diabetes and their condition is recorded in the dataset. Whilst there may be some false negatives it is unlikely that there are any false positives, so it may be possible to conduct analysis assuming that a no-response indicated being free of the disease, which would lead to conservative results.

The final variable in the time-preference framework was whether the individual is a hyperbolic discounter (Fan and Jin, 2013). As it is impossible for Slimming World to collect data on whether an individual is a hyperbolic discounter a proxy will need to be used. Eisenhauer and Ventura (2006) showed a negative relationship between educational attainment and hyperbolic discounting and so education IMD score will be used as a proxy again. Older people are likely to have more motivation to manage weight, with Grunert et al. (2012) hypothesising that this is because the health effects from their obesity is likely has a shorter delay due to health consequences usually becoming apparent in later life. This results in more risk in the next period, which is an example of preferences changes depending on the time period. For example, the risk of developing type 2 diabetes and suffering from heart disease increase with age (Pippitt et al., 2016; North and Sinclair, 2012). Therefore, age (a_i) was used as a proxy for hyperbolic discounting.

Appendix 6 shows a summary of the hypotheses and variables used in the time-preference framework.

5.1.3 Habits and Self-Control

The habits and self-control theoretical framework, displayed in Equation 19, contained 7 variables, with 5 of the variables influencing either the individual's self-control (SC_i) or strength of habits (hab_i). Self-control is a function of the individual's investment in the programme (inv_i), which is itself a function of whether the individual is sophisticated about their self-control issues (sop_i), and whether the individual has replaced their overeating with an alternative activity (alt_i). Strength of habit is a function of the total number of past-diets the individual has attempted (pd_i,) and the individual's stock of past over-consumption of food (poc_i). Again, not all these variables were present in the Slimming World dataset and so proxies were selected.

Equation 19

$$\Delta W_i = SC_i(inv_i(sop_i), alt_i) - hab_i(pd_i, poc_i)$$

Equation 20 shows the empirical framework for habits and self-control. A proxy for the level of investment in the programme was taken from a categorical variable – the individual's join type (M_i), as each membership has a different upfront cost (Djawadi et al., 2014).

Equation 20

$$\Delta W_i = \beta_0 + \beta_1 M_i + \beta_2 c_i + \beta_3 r_i + \beta_4 (BMI_{B,i} - 25) + \varepsilon_i$$

As sophisticated individuals are those that employ strategies to generate commitment to the programme, it was assumed that those who purchase a Countdown ($\boldsymbol{c_i}$) (an upfront payment for either 6 or 12 weeks of classes) reveal themselves to be sophisticated rather than naïve (Dodd, 2008); signaling a generation of commitment at Slimming World. One problem with this proxy was that it is likely more wealthy members can afford this than those that are less well off. Another potential problem was that as there is a discount at Slimming World for purchasing a Countdown, some individuals may purchase them for the discount rather than commitment reasons. Even taking these points into consideration, the upfront payment is likely to motivate individuals to put more into the programme as they know they are paying regardless of whether they attend or not.

For the alternative activity variable, as it is unknown what people do outside classes, it is impossible to know whether people are replacing eating with alternative activities and therefore it was impossible to create a suitable proxy using the Slimming World dataset (Buscemi et al., 2014).

As strength of habit is unmeasurable, proxies had to be used to make assumptions about which groups have the strongest habits and who has the most difficulty changing their routines and maintaining the change (Dragone, 2009). The first influencer on strength of habit is the number of past-diets (Rosin, 2012). The proxy variable chosen was whether the individual had been a member of Slimming World pre-2014 (r_i). This indicates that the individual has tried to lose weight in the past and that they have struggled to make a long-term change to their habits which has led to them re-joining Slimming World's weight management programme. If it is assumed that individuals who were members of the Slimming World programme before 2014 have had more diet attempts then predictions can be made future weight management success. A limitation of using this a proxy was that the assumption is made that only those who have rejoined the programme have attempted weight-loss before, and it is unlikely these individuals are the only members to have attempted weight loss in the past. However, joining the Slimming World programme is a different method of weight-loss attempt and so the proxy may still be valid.

The second influencer of strength of habit was past-overconsumption as the more over-consumption the individual has engaged in, the stronger their poor weight management habits are likely to be, and therefore the more difficult they are likely to find changing their lifestyles in the long-term to be. The stock of past-overconsumption was unavailable in the Slimming World dataset, but as overconsumption of food causes weight gain, those who have overconsumed the most in the past are likely to have the largest BMIs (Becker and Murphy, 1998). Therefore the proxy for past-overconsumption chosen was how overweight the individual is – the difference between their BMI and a BMI of 25.

Appendix 7 shows a summary of the habits and self-control theories and variables.

5.1.4 Overall Empirical Specification

The final step before moving into the methods of implementing the empirical specification was to combine the three themes into one overall specification to explain weight management. The first reason for doing this is that individual decisions regarding weight management are likely to be influenced by rational choice, time-preference and habits and self-control simultaneously. Another reason for this combination is that due to the limited number of variables and the necessary use of proxies, there was overlap between the variables used in each framework. Given the overlap one single framework should be able to explain weight change more effectively than any one theme alone, Equation 16, Equation 18, and Equation 20 were combined into the specification in Equation 21. According to the theoretical framework, and the literature regarding the proxies, each of the variables in the empirical specification should contribute toward explaining weight change.

Equation 21

$$\Delta W_i = \beta_0 + \beta_1\left(W_{0,i} - W_{x,i}\right) + \beta_2 I_i + \beta_3 P_i + \beta_4 C_i + \beta_4 J_i + \beta_5\left(BMI_{B,i} - 25\right) + \beta_6 R_i + \beta_7 D_i + \beta_8 (A_i * E_i) + \beta_9 E_i + \beta_{10} a_i + \beta_{11} M_i + \beta_{12} c_i + \beta_{13} r_i + \varepsilon_i$$

5.1.5 Summary of Empirical Specification

The aim of this section was to relate the theoretical frameworks from Chapter 3 to the variables available in the Slimming World dataset. The theoretical frameworks have provided rationale for which variables should be included in predictive modelling of weight change.

Whilst some of the hypotheses that have been formed have been intuitive, there are a number of contrasting predictions. For example, the prediction that individuals that have joined through a referral will lose more weight, as they have met with a GP to discuss the risks of obesity and therefore are better informed. Conversely, referral members have not paid any initial fee to join the Slimming World programme and therefore have smaller losses to compensate, which, theoretically, leads to them discontinuing the programme earlier than someone that has paid to participate in the programme. These two hypotheses therefore contradict each other regarding the impact of joining the Slimming World programme by the GP referral pathway.

Another variable that the theories predict conflicting effects on weight loss was baseline weight or BMI. Rational addiction theory suggests that people that are more overweight have a larger stock of past consumption, they will find it more difficult to change their habits and lose weight. However, utility theory suggests that as these individuals are further from their target weight, they will also have a larger utility loss from their weight. Overall, these two effects may somewhat negate each other. What may be expected is that those who are most overweight are able to lose weight initially as they have more to lose and are more motivated, but struggle to maintain this weight loss as their habits are too strong to change in the long-term.

A further consideration when running the analysis is that there may be correlation between variables. This can be problematic. Collinearity can increase standard errors of coefficients and limit the accuracy of estimations made in regression modelling (Gujarati, 2003). The first of the correlated variables are the difference between baseline weight and target weight, and baseline BMI and a healthy BMI. This is because BMI is derived directly from weight, and target weights are likely close to a healthy weight. The next potential correlation is between having partner at home and having children at home as it is likely that many members that have partners will have children and vice versa. Whether the individual has diabetes and age may also be a problem as the prevalence rate for diabetes increases with age. Education IMD and income IMD may also be correlated as those who are more educated generally earn higher wages (Tamborini et al., 2015).

The next section will discuss the regression methods that will be used to test the empirical framework and make predictions regarding weight change.

5.2 Regression Methods

Now that the empirical framework has been set out, the methods for testing theoretical hypotheses and making predictions about weight trajectories will be discussed. The Slimming World data discussed in Chapter 4 will be used to estimate parameter values and predictions regarding outcomes. Data analysis was performed using STATA 13.1 (StataCorp, 2013).

First, the initial 12-week programme at Slimming World will be used to test the theoretical framework before moving onto what influences whether individuals continue attending Slimming World classes after the first 12 weeks and making predictions about who continues attending. These predictions will then be used to make further predictions about long term weight trajectories.

After estimations using the 12-week outcomes have been analysed, parameters associated with likelihood of continued attendance will be estimated. These will then be combined to give an understanding of what may happen after the 12-week programme.

The first of the methods that will be used to test the theoretical framework is the most common form of linear regression - OLS.

5.2.1 Method 1: Ordinary Least Squares

The aim of OLS is to model the relationship between the dependent variable, in this case weight change, and the independent variables, which are the predictors of weight change, for example age and income. The regression model is a linear function of the independent variables plus a random component. Using OLS, it is possible to estimate the coefficient attached to each independent variable, which represents the effect that a one unit change has on the dependent variable. The sign of the independent variables describes the direction of the effect on the independent variable. In the case of dummy variables, the coefficients shift the intercept of the regression curve. Parameters should be chosen with the aim of minimising the residual sum of squares and maximising R^2, which states the proportion of the variance in the dependent variable that is explained by the explanatory variables. OLS regression will be used to estimate the coefficient values and forecast weight change in a linear regression model that represents the full theoretical model (Verbeek, 2012).

According to the Gauss-Markov Theorem, linear regression where errors have zero expected mean, are uncorrelated and have homoscedastic variance is regarded as being the best linear unbiased estimators. If the assumptions of OLS are not held, bias can be introduced into the model and estimates can be inaccurate. If this is the case, another form of linear regression – GLMs can be used as an alternative as they are bound by less assumptions.

5.2.2 Generalised Linear Model

GLMs rely on maximum likelihood estimation rather than the sum of squares, as is the case in OLS estimation and can be fit to non-linear relationships using a link function. There are three components to a GLM model.

1) The random component
2) Systematic component
3) Link function between 1) and 2)

The random component is the probability distribution of the response, or outcome variable (Y). The response variable has a normal distribution and it is assumed that the error term is normally and independently distributed with a mean of 0 and a standard deviation of σ. The systematic component of a GLM is the predictor variables (Xs) which are combined to create the linear predictor which predicts the response variable. The third part is the link function which is used to connect the predictors to the outcome and can be used in situations where the predictors are not linearly related to the outcome variable. The link function explains how the expected outcome relates to the linear predictor.

For a linear function Equation 22 shows the link function (η), whilst Equation 23 shows the link function for a non-linear logistic regression.

Equation 22

$$\eta = g(E(Y_i) = E(Y_i)$$

Equation 23

$$\eta = logit(\pi)$$

5.2.3 Method 2: Probit Model

In a probit model, the dependent variable can take only one of 2 possible values – the probability that the outcome is either true or false (Liao, 1994). Therefore probit models cannot predict the magnitude of weight change.

Equation 24

$$Pr(Y = 1|X) = \phi(X^T\beta)$$

Equation 24 represents the probability of the outcome being true given the explanatory variables. $\phi(X^T\beta)$ represents the cumulative distribution function of a normal distribution – the explanatory variables and coefficient values estimated by maximum likelihood estimation.

In a probit model, a 1 unit increase in X results in a β% increase in Y. In order to find probability, the outcome variable must be transformed from one that is dichotomous to one that is continuous. The function then becomes which turns the outcome variable to one that can only take the form of 0 or 1 to one that becomes a probability between 0 and 1. The probit model uses the link function shown in Equation 25.

Equation 25

$$F(Y) = Y' = X\beta + \varepsilon$$

This function is found by the following method shown in Equation 26, Equation 27, and
Equation 28, where the outcome is equal to the cumulative normal distribution,ϕ, of the explanatory variables and the coefficient plus the error term.

Equation 26

$$Y = \phi(X\beta + \varepsilon)$$

Equation 27

$$\phi^{-1}(Y) = X\beta + \varepsilon$$

Equation 28

$$Y' = X\beta + \varepsilon$$

So in this case the probit link function is shown in Equation 29.

Equation 29

$$F(Y) = \phi^{-1}(Y)$$

After estimation, probabilities can be found using standard normal distribution, where the independent variables and the coefficient values correspond to a Z-score($X\beta = Z$). The cumulative normal distribution,ϕ, can take any z score,

$\phi(Z) \in [0,1]$. A 1 unit change in X_i causes a β_i change in the z-score of Y. This creates a non-linear cumulative distribution which can fit better than a linear regression, and, in this case, give a probability of whether the individual reaches their target weight, 3%, 5% or 10% weight loss and whether that weight loss is maintained at 12- and 24-months.

5.2.4 Method 3: Heckman Specification Model

The final method that will be employed is a two-part model – the Heckman correction. Heckman makes the assumption that missing values of the dependent variable imply that the dependent variable is unobserved (people didn't make the attendance). For individuals that did not attend the programme in the last week of the programme, LOCF as an outcome holds some uncertainty as there is the question of whether individuals continued losing weight after the left the programme, whether they maintained their weight loss or whether they gained weight. The level of uncertainty is reasonably small in the analysis at 12-weeks, but when reviewing weight-change outcomes at 6 months, 12 months and 24 months, the level of uncertainty increases. In Heckman, it is essential that in the selection equation, there are variables included that predict whether the individual is selected but are not included in the regression equation predicting the outcome variable. This model corrects for selection bias which may be present in the data that Slimming World has provided. As individuals are only weighed by Slimming World when they attend classes, there is selection bias in that the data will only be available for those that attend classes and are engaged with the programme. This means that the samples are non-randomly selected, estimation of parameters only using these individuals can cause selection bias is present as those that attend classes are likely to lose and maintain more weight than those that stop attending (Jin, 2016).

In order to correct for this bias, a control function is implemented. This part of the model assumes a probit regression, as in method 2, where the probability of being observed is calculated by the formula in Equation 30 which states the probability of attending (A), which is condition on a vector of explanatory variables (Z) is equal to the cumulative distribution function, ϕ, of a vector of explanatory variables and a vector of unknown parameters (γ). The estimation yields a prediction of the probability of each individual completing the programme.

Equation 30

$$Pr(A = 1|Z) = \phi(Z\gamma)$$

The second stage of the model involves correcting for selection bias by transforming the predicted probabilities into an additional explanatory variable which is then incorporated into an equation to predict weight change. Conditional expectation of weight change for an individual that attends is given by Equation 31.

Equation 31

$$E[\Delta W|X, A = 1] = X\beta + E[\varepsilon|X, A = 1]$$

The equation shows that the expected weight change (ΔW) which is conditional on the explanatory variables and that the individual is observed is equal to the coefficient and the explanatory variables plus the conditional expected error term.

The Heckman-correction regression model was chosen for analysis because it was judged to be the most appropriate method of predicting data for participants that had unobserved outcomes, as it uses the observed sample to predict non-biased estimates for the non-observed sample.

In the Slimming World programme, participants who are observed are those that are most engaged in the programme, as they have continued attending Slimming World classes. As attendances have been shown to positively influence weight-loss, it is likely that those who continue to attend, lose more weight than those who stop attending. Therefore, there is a systematic difference between the outcomes of those who are observed and unobserved, which means that the data is missing not at random, and selection bias is present (Sterne et al., 2009). Because of this, consideration for this selection bias has to be made when making predictions of outcomes for the non-observed sample using data from the observed sample (Jackobsen et al., 2017).

Complete case analysis, single imputation, and multiple imputation were also considered to account for missing data (Jackobsen et al., 2017). However, these were decided to be suboptimal. Complete case analysis was not appropriate as the vast majority of people do not attend Slimming World for the full 24-month period and so the analysis would be very limited, and the data in the remaining sample would not be missing at random and so would not representative of all Slimming World participants (Pigott, 2001). For imputation to be appropriate, data must be missing at random, which means that there is no systematic reason for those with missing data to have different outcomes to those without missing data (Jackobsen et al., 2017). Due to the data being missing not at random, imputation would be biased, as imputed values would be based on the outcomes of individuals who are still attending the Slimming World programme and engaged with their weight-loss. Therefore, imputation was not appropriate for this data analysis.

Because the data for individuals who leave the Slimming World programme are unobserved, it is difficult to judge the validity of predictions of their weight-change. Judgements of validity must therefore be based on how plausible the results are.

5.3 Results

5.3.1 Univariate Analysis

The first step to regression analysis was to perform univariate analysis using OLS regression where each of the explanatory variables was run in a regression with the outcome being LOCF weight change at the 12th Slimming World class, which is referred to as 'week 11'. This was to analyse the univariate relationships between each of the explanatory variables and the outcome variable. In each of the regressions, baseline weight was used as a control variable so the effects of each variable on weight-change was independent of starting weight. The coefficient values are shown in Table 23. To illustrate the effect of using a categorical variable for income IMD and education & skills IMD quintiles, analysis was performed twice – once with these two variables as continuous variables, and once inputting these two variables as categorical variables, and results were added to the Appendix.

Corresponding tables for regression results using categorical IMD variables are highlighted in the table titles for the remainder of this chapter.

Table 23: Univariate Regression Results Predict LOCF Weight-Change with Baseline Weight as a Control Variable (Appendix *8*)

Variable	n	Coefficient	t-statistic
Target Weight Change (kg)	554,300	0.0216***	45.37
Income IMD Quintile (0: most deprived, 4: least deprived)	510,082	-0.0577***	-18.55
Partner at Home (1=yes, 0=no)	252,321	-0.393***	-28.45
Children at Home (1=yes, 0=no)	252,321	-0.0720***	-5.83
Employment Status (1=part-time, 0=full-time)	252,321	-0.119***	-9.01
Diabetic (1=yes, 0=no)	692,945	-0.362***	-15.17
Full Attendances	692,945	-0.513***	-530.93
Education and Skills IMD Quintile (0: most deprived, 4: least deprived)	516,796	-0.0198***	-6.37
Age at Start Date (years)	692,945	-0.121***	-45.90
Join Type (re-join=1, standard=0)	451,912	1.891***	211.14
Join Type (countdown=1, standard=0)	371,340	-0.127***	-9.65
Join Type (discount, standard=0)	427,251	0.491***	47.81
Join Type (referral=1, standard=0)	325,361	-0.472***	-19.85

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

Table 23 shows that each variable was significant at the 0.1% level. Key drivers of weight loss were setting a more ambitious target, living in a less deprived area in terms of both income and education, having a partner and/or children living at home, having a part-time job rather than a full-time job, attending more Slimming World classes, being diabetic and being older. Joining Slimming World via SWoR or a countdown predicted a greater weight loss than joining a standard membership, whilst joining via a discount code or re-joining the Slimming World programme predicted less weight loss after 12-weeks.

As well as this, the same regressions were run using total attendances in the initial 12 week period as a control variable to review the effect magnitudes of each variable if the effect of the variables on attendances is nullified. The results are shown in Table 24.

Table 24: Univariate Regression Results with Baseline Weight and 12-Week Attendances as Controls (Appendix *9*)

Variable	n	Coefficient	t-statistic
Target Weight Change (kg)	554,300	0.0225***	62.14
Income IMD Quintile (0: most deprived, 4: least deprived)	509,926	-0.0197***	-8.20
Partner at Home (1=yes, 0=no)	252,321	-0.120***	-11.58
Children at Home (1=yes, 0=no)	252,321	-0.120***	-13.03
Employment Status (1=part-time, 0=full-time)	252,321	-0.00421	-0.43
Diabetic (1=yes, 0=no)	692,945	0.0586**	3.19
Full Attendances	692,945	-0.0880***	-61.73
Education and Skills IMD Quintile (0: most deprived, 4: least deprived)	516,796	-0.00737**	-3.07
Age at Start (years)	692,945	0.00632***	30.78
Join Type (re-join=1, standard=0)	451,912	1.189***	171.26
Join Type (countdown=1, standard=0)	371,340	0.473***	48.42
Join Type (discount, standard=0)	427,251	0.494***	65.36
Join Type (referral=1, standard=0)	325,361	0.458***	26.37

$P<0.05$*, $p<0.01$**, $p<0.001$***

The impact of including the number of attendances as a control variable is a reduction in the coefficient value for most explanatory variables. This is due to those variables that are significant predictors of weight-change also being significant predictors of attendance within the first 12-weeks. Introducing attendances as a control variable switched the sign of some coefficient values – namely the coefficient for diabetes, age, countdown and referral. This means that while these variables were all significant predictors of a greater weight-loss at 12-weeks, they were stronger predictors of attendance and, given a fixed number of attendances, these variables predict less weight-loss.

The impact of full attendances has been greatly reduced, but the positive effect of not leaving classes early is still prevalent, with each IMAGE therapy session providing a further loss of 0.09kg over 12 weeks.

5.3.2 Full Linear Regression Model

The model selection approach used was a general-to-specific approach which entailed starting the selection process with all variables that were found in the theoretical framework (Campos et al., 2005). The general model used Equation 21 as a starting point but some adjustments were made in order for the model to be effective. The first adjustment was that full attendances and education and skills IMD quintile were included separately due to difficulty in interpreting the coefficient and no benefit to the explanatory power of the regression model. Another adjustment made was the various join types were all included as one categorical variable for practicality reasons. The variable for the difference between baseline BMI and a healthy BMI was also removed due to its similarity with the target weight-loss variable. As well as this, to identify the effect of IMAGE therapy on weight-change with the full attendances variable, the total number of attendances in the first 12 weeks was included in the model.

The final change to the regression model was that the three variables taken from the employment form – partner at home, children at home, and employment status – were dropped from analysis. This was for two reasons. The first was that the sample size was reduced as a large proportion of sample members did not complete the employment form. The second was that the employment form was optional, and only completed by individuals that were in full-time or part-time work. Therefore, data regarding whether the individual has a partner or children was missing if the individual was unemployed, or chose not to complete the form. Baseline weight and gender were then included as a control variable to ensure the result was independent of these two factors.

Before running the regression model, the relationships between each variable were reviewed in order to make sure that the explanatory variables all held linear relationships with the dependent variable, LOCF weight change at 3 months, in order to avoid any specification error (Baum, 2006). When reviewing each relationship, no clear non-linear trends were identified between weight-change and any of the explanatory variables. The model was then run in STATA to create the output in Table 25. Only individuals with full data across all explanatory variables in the model were included in analysis.

Table 25: Multivariate OLS Regression Model to Predict LOCF Weight-Change at 12-Weeks (Appendix *10*)

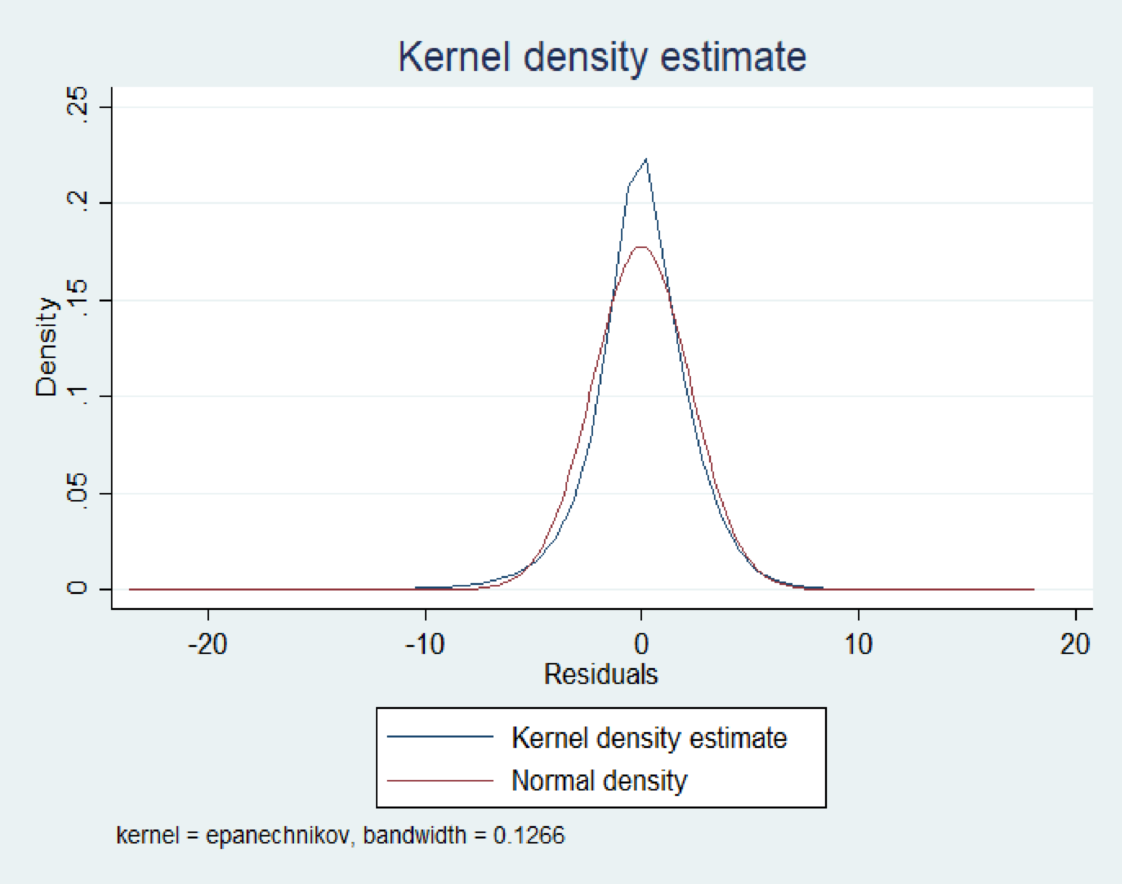
Variable	Coefficient	t-statistic
Target Weight Change	0.0192***	45.36
Income IMD Quintile	-0.0409***	-9.00
Diabetic	0.342***	15.25
Full Attendances	-0.109***	-61.10
Total Attendances	-0.517***	-296.51
Education and Skills IMD Quintile	0.0104*	2.27
Age at Start Date	0.00486***	17.86
Standard Join Type	0	.
Rejoin Join Type	1.140***	107.17
Countdown Join Type	0.371***	31.54
Discount Join Type	0.385***	38.86
Referral Join Type	0.315***	16.24
Baseline Weight	-0.0299***	-132.27
Male	-1.125***	-64.23
Constant	3.667***	155.95
N	393,318	

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

All variables included in the regression model in Table 25 were significant predictors of LOCF weight-loss at 12-weeks at the 0.1% level, other than education and skills IMD quintile which was significant at the 5% level.. No further variables were removed from the regression model. The model produced an R^2 value of 49.57% which means just under half of the variance in weight-change was explained by the model. When holding all else constant setting a more ambitious target continued to predict more weight-loss. Interestingly, when holding all other variables constant, individuals with diabetes lost significantly less weight which may imply that although individuals with diabetes may have more motivation to lose weight, dietary restrictions may hamper their ability to lose weight. Attendances were the largest predictor of weight loss with each attendance predicting over half a kilogram of additional weight loss. Attending a class and staying for IMAGE therapy predicted an additional 0.11kg of weight loss for each full attendance. When holding all variables constant, participants that joined on standard memberships lost the most weight in the initial 12-week period. This implies that the benefit of purchasing a countdown or being referred to Slimming World does not include a greater motivation to lose weight holding all other variables constant.

After the regression model was run in full, residuals were then plotted to identify the distribution and check for normality (Miller, 1997). The first is a kernel density plot of the residuals against a normal distribution, shown in Figure 11. The plot shows a close to normal distribution with a higher peak.

Figure 11: Kernel Density Estimate for Residuals of the OLS Regression



Following this, the quantile of the residuals were plotted against the quantiles of a normal distribution, which is shown in Figure 12, below. Here, the plot deviates from the normal distribution at the tails. The normal probability plot in Figure 13, shows a closer to normal distribution with small deviations from normal in the middle of the plot.

Figure 12: Q-Q Normality Plot for the OLS Regression

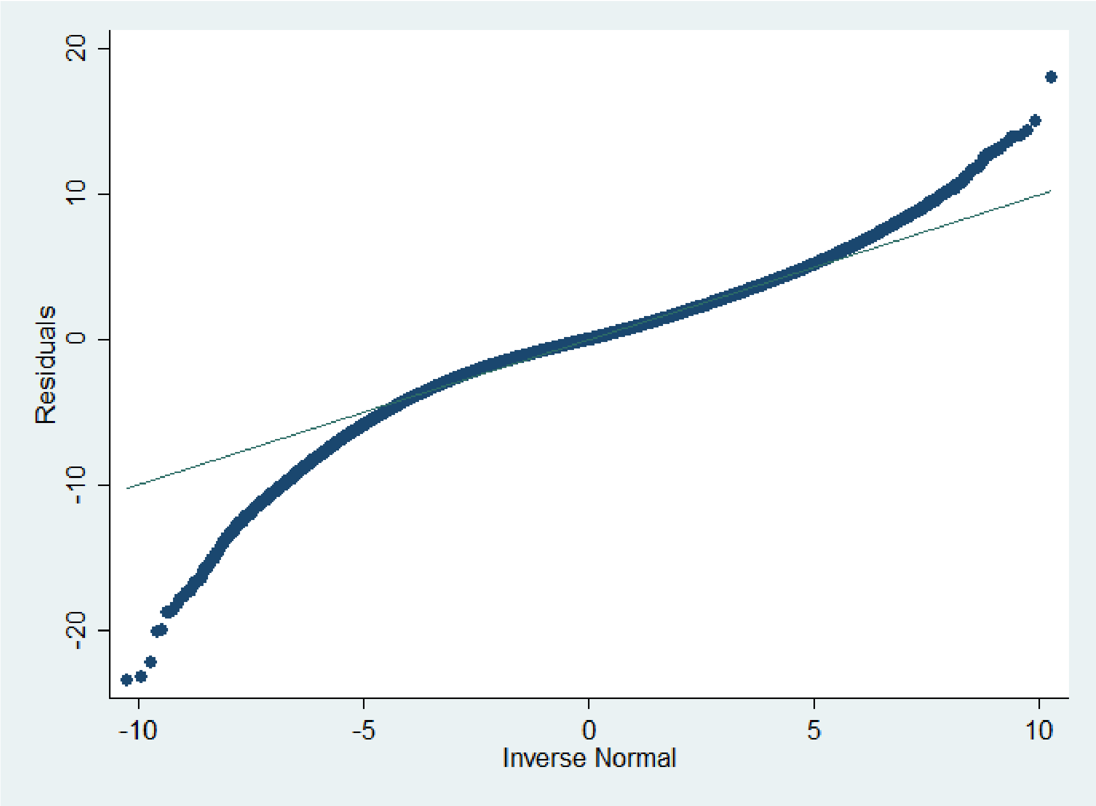


Figure 13: P-P Plot for the OLS Regression

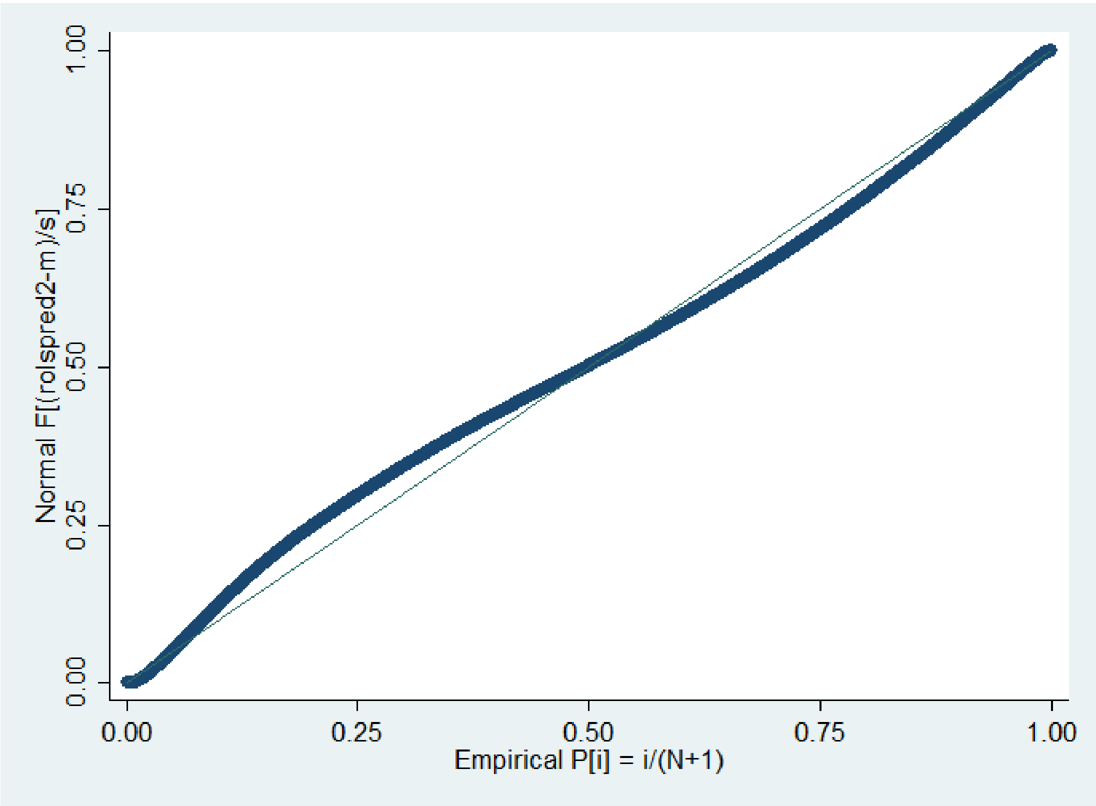
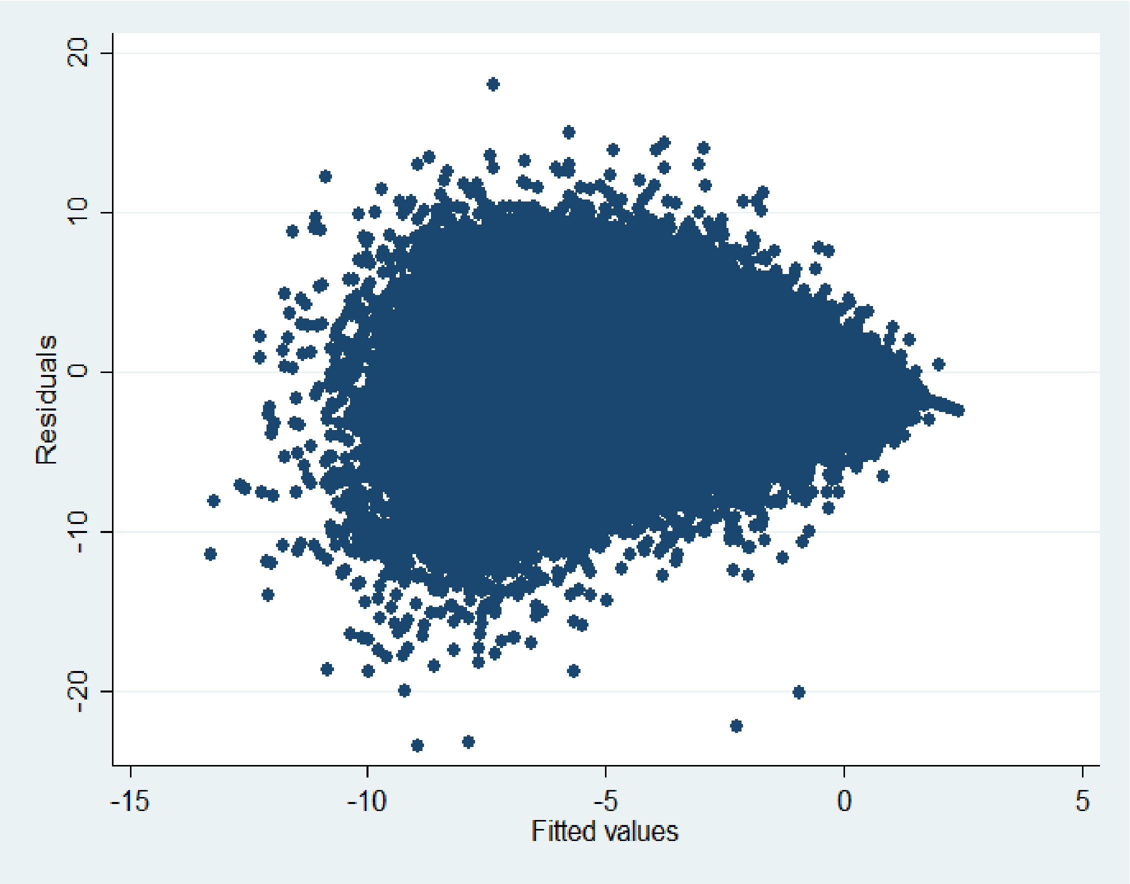


Figure 14 shows a plot of the residuals against the fitted values from OLS regression model 1. The plot shows that although the residuals have a slightly greater variance as the fitted values get smaller, the plot does not reveal a concerning level of heteroscedasticity. Overall, the deviations from normality are not pronounced enough to make any hypothesis testing invalid, especially given the sample size.

Figure 14: A Plot of Residuals against Fitted Values for the OLS Regression



The final diagnostic test was for collinearity. In multivariable regression, the efficiency depends on correlation between the explanatory variables, as linear regression assumes that explanatory variables are uncorrelated (Woo et al., 2014). To test whether problematic collinearity was present within the regression model, VIF scores were investigated. VIF indicates the extent to which coefficients are inflated due to collinearity and provides a score indicating the amount of collinearity present. Woo et al. (2014) state that it is generally accepted that a VIF score of above 10 may be harmful within a regression model.

When checking the VIF scores for each coefficient, no problematic collinearity was identified with the highest VIF score being for income IMD quintile and education and skills IMD quintile, which were both 3.01.

As attending classes indicates programme engagement, and is an outcome in itself, the OLS model was also reviewed without either the total attendances or full attendances variables to highlight the impact of each variable on weight-change. The R^2 statistic fell to 13.00% which implies that much of the variance in weight-change was explained by attendance, but some of weight-change could be explained by participant characteristics at baseline. The output is shown in Table 26, below.

Baseline age was one variable where the coefficient sign changed from positive to negative. This implies that age is likely a better predictor of increased attendances than weight loss, as when controlling for attendance, being older no longer predicts more weight loss. Countdown and Referral join types saw a similar pattern, with both signs changing from positive to negative. Other than these three variables, all other predictors did not change sign, and so are consistent predictors of both attendance and weight-loss.

Table 26: The OLS Regression Model without Attendance Data (Appendix *11*)

Variable	Coefficient	t-statistic
Target Weight Change	0.0195***	35.01
Income IMD Quintile	-0.0958***	-16.06
Diabetic	0.337***	11.43
Education and Skills IMD Quintile	0.0693***	11.54
Age at Start Date	-0.0155***	-43.88
Standard Join Type	0	.
Rejoin Join Type	1.818***	131.10
Countdown Join Type	-0.154***	-10.02
Discount Join Type	0.297***	22.92
Referral Join Type	1.818***	-17.90
Baseline Weight	-0.0343***	-115.90
Male	-1.286***	-56.82
Constant	0.361***	12.18
N	393,318	

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

5.3.3 Probit Model

After the relationships between characteristics and LOCF outcomes at the end of the 12-week programme were assessed, the next stage of analysis was to use a probit model to review the influencers of attendance in week 11 – the final session of the initial 12-week programme, and continued attendance after the initial 12-weeks. The regression output is shown in model 1 in Table 27, with the same explanatory variables used as in the OLS model predicting weight-change. The model was also run without the two attendance variables, as week 11 was within the initial 12-weeks, as without these two it is clearer to see which variables are predictors of attending until the end of the programme without knowledge of earlier attendances. This output is shown in model 2 in Table 27.

The probit model found that similar variables predicted whether an individual would attend in week 11 of the Slimming World programme, and how much weight-loss an individual would achieve after 12-weeks. Setting a more ambitious target, being in an area of less income deprivation and being older predicted an improved likelihood of completing the 12-week programme. Being in an area of less education and skills deprivation had a small positive effect on the likelihood of attendance when including attendances as an explanatory variable, but predicted a lower likelihood of attendance without controlling for attendances in the first 12-weeks. In terms of join type, those who re-joined the programme were much less likely to be a completer, whilst joining via a countdown, discount or referral predicted an increased chance of completion. Whilst model 2 revealed the relationships between individual characteristics and attendance in week 11 independent of previous attendances, model 1 was more predictive, with a pseudo R^2 of 54.83% compared with 2.63% in model 2. According to the F-statistic, both models were found to be statistically significant predictors of attendance at the 0.1% level.

Table 27: Probit Regression Model predicting Attendance in Week 11 (Appendix *12*)

Variable	Coefficient (model 1)	t-statistic (model 1)	Coefficient (model 2)	t-statistic (model 2)
Target Weight Change	-0.0000719	-0.21	-0.000566*	-2.35
Income IMD Quintile	0.00532	1.44	0.0325***	12.52

Diabetic	0.0113	0.63	0.00984	0.78
Full Attendances	0.0217***	17.20		
Total Attendances	0.546***	281.17		
Education and Skills IMD Quintile	0.00961*	2.58	-0.0305***	-11.69
Age at Start Date	0.00124***	5.71	0.0105***	68.16
Standard Join Type	0	.	0	.
Rejoin Join Type	0.0860***	9.50	-0.362***	-57.70
Countdown Join Type	0.0530***	5.93	0.211***	32.19
Discount Join Type	0.0445***	5.52	0.0401***	7.15
Referral Join Type	0.124***	8.42	0.425***	38.87
Baseline Weight	0.000413*	2.24	0.00207***	16.10
Male	0.0156	1.15	0.0917***	9.40
Constant	-5.281***	-219.81	-0.925***	-71.45
N	393,318		393,318	

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

The next variables of interest to predict were whether individuals made an attendance after the initial 12-week period, is whether an attendance was made more than 6-months from joining, and whether an attendance was made over a year after joining the Slimming World programme. The regression outputs are shown in Table 28, below, with model 1, 2 and 3 predicting attendances after 12-weeks, 6-months and 1-year. For attendance after 6-month and attendance after 1-year, predicted values of attendance after 12-weeks and after 6-months were included as explanatory variables. Model 1 produced a pseudo R^2 value of 56.24% whilst model 2 and 3 reported values of 35.99% and 27.90% respectively, which is intuitive as the level of uncertainty rises over time. Again, according to the F-statistic, all three models found the explanatory variables were significant predictors of attendance at the 0.1% level.

Being in a higher income IMD Quintile and being older were both positive influencers of probability of attendance after each of the 3 time points. Education and skills IMD quintile did not have any significant effect on probability of attending at 6-months or 1-year. Joining Slimming World via a countdown membership predicted a significantly higher likelihood of attending after 12-weeks, but did not have an impact at 6-months or 1-year. Those who re-joined the Slimming World programme, or joined via a discount code or referral were significantly less likely to still be attending Slimming World classes after 6-months and 12-months. With regarding to engagement in the first 12-weeks, those who attended more sessions were significantly more likely to continue attending after each of the three time-periods, but the effect declined over time. However, the effect of each additional full-attendance was a greater predictor of increased attendance at both 6-months and 1-year than at 12-weeks, implying that those who are most engaged with the programme initially, and stay for IMAGE therapy, are significantly more likely to continue attending in the long-term.

Table 28: Probit Regression Models Predicting Attendance at 12-Weeks, 6-Months and 1-Year (Appendix *13*)

Variable	Coefficient (12-Weeks)	t-statistic (12-Weeks)	Coefficient (6-Monts)	t-statistic (6-Months)	Coefficient (1-Year)	t-statistic (1-Year)
Target Weight Change	-0.000146	-0.42	-0.000304	-0.97	-0.0000250	-0.07
Income IMD Quintile	0.0244***	6.66	0.0317***	9.42	0.0174***	4.57
Diabetic	-0.0305	-1.66	-0.0179	-1.15	-0.00556	-0.33
Full Attendances	0.0572***	42.50	0.0815***	67.84	0.0596***	27.83
Total Attendances	0.463***	286.08	0.241***	43.40	0.109***	15.64
Education and Skills IMD Quintile	0.0135***	3.68	-0.00337	-1.00	-0.00721	-1.90
Age at Start	0.00554**	25.42	0.00834***	41.03	0.00779***	29.07
Standard Join Type	0	.	0	.	0	.
Rejoin Join Type	0.0125	1.46	-0.126***	-14.61	-0.133***	-12.51
Countdown Join Type	0.0857***	9.45	-0.00933	-1.16	0.0100	1.14
Discount Join Type	-0.0153	-1.91	-0.0540***	-7.40	-0.0488***	-5.91
Referral Join Type	0.0280	1.82	-0.193***	-15.02	-0.0422**	-2.96
Baseline Weight	0.00134***	7.33	0.00204***	12.24	0.000900***	4.77
Male	0.0344*	2.49	-0.00537	-0.44	-0.0413**	-3.08

Attendance after 12-Weeks	-	-	0.468***	10.73	0.180***	3.65
Attendance after 6-Months	-	-	-	-	1.210***	22.54
Constant	-4.530***	-209.70	-4.155***	-121.40	-3.538***	-69.69
N	393,318		393,318		393,318	

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

5.3.4 Heckman Selection Model

After the probit regression models were run, the final stage to predicting weight-change outcomes for the Slimming World population was to use the Heckman correction to predict weight-change conditional on attendance at various time-points. The first model was a two-step model, created to predict weight-change at the end of the 12-week programme, conditional on whether the individual attended the week 11 session, which was the final session within the initial 12-week period. The prediction of whether the individual attended in week 11 was taken from the probit model 1 in Table 27, shown previously.

For the outcome equation predicting weight-change at week 11, the selection equation must have at least one variable that is not present in the outcome equation. In this case join-type and total attendances were removed from the equation. This was because join-type and attendance without IMAGE therapy were identified to have a stronger association with attendance than weight-change. The regression output for the Heckman correction model predicting weight-change at week 11, in Table 29, was similar to the OLS model predicting LOCF weight-change at 12-weeks. Target weight change, less income IMD deprivation and attendances all continued to be significant predictors of more weight-loss. The selection output is shown in Appendix 14.

Table 29: Heckman Selection Model Predicting Weight-Change at Week 11 with Attendance at Week 11 as the Selection Outcome (Appendix *15*)

Variable	Coefficient	t-statistic
Target Weight Change	0.0351***	39.03
Income IMD Quintile	-0.0773***	-7.92
Diabetic	0.291***	6.63

Full Attendances	-0.107***	-34.64
Education and Skills IMD Quintile	0.0393***	4.00
Age at Start Date	0.0106***	18.82
Baseline Weight	-0.0463***	-96.12
Male	-1.439***	-41.74
Constant	-1.136***	-20.32
N	393,318	

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

*Selection output omitted

Table 30 shows values for LOCF weight-change, the predicted weight-change from the OLS model with attendance data, and the Heckman correction model predictions for weight-change at week 11, the end of the 12-week programme. Each of the three values are very similar for those that attended the final Slimming World class, which is understandable as there is very little uncertainty. However, differences arise in those who didn't attend the final Slimming World session. The OLS model predicted a very similar mean LOCF weight-change for non-attenders as the LOCF weight-change, at just over -2.2kg.

The Heckman correction model predicted a weight-loss of over 6kg across the full sample at 12 weeks, which may be optimistic, as the model has predicted that those who do not attend the 12th session, in week 11, have continued losing weight outside the programme. This is due to the model having no information regarding any weight-change outcomes for those who are unobserved, and the model having to base predicted weight-change on the outcomes of those who are observed. Whilst the model has predicted that those who do not attend lose less weight at 12-weeks, it appears as if the difference between the two groups has been underestimated, if this assumption is that those who do not attend do not lose weight, or, lose less weight than those who attend. This is likely an invalid estimation of weight-change as it is unlikely that on average, those who leave the programme will have lost a substantial amount more at 12-weeks.

Table 30: LOCF Weight-Change and Predicted Weight-Change at Week 11 (Appendix *16*)

Group	N	LOCF Weight-Change (kg)	OLS Model Prediction of LOCF Weight-Change (kg)	Heckman Correction of Weight-Change at Week 11 (kg)
Full Sample	393,318	-3.499 (3.167)	-3.499 (2.230)	-6.112 (1.300)
Attended Week 11	155,230	-5.376 (3.340)	-5.357 (1.340)	-6.410 (1.322)
Did Not Attend Week 11	238,088	-2.275 (2.346)	-2.288 (1.824)	-5.918 (1.247)

*standard deviation in parentheses

5.3.5 Heckman Selection Model Predictions of Weight-Change at 6, 12 and 24 Months

Following predictions at 12-weeks, the Heckman correction was then used to make predictions regarding weight-change at 6-months, 1-year, and 2-years, with the aim of making predictions regarding the weight-change of non-attenders more accurate than LOCF weight-change. To do this, predictions were made regarding LOCF weight-change using the two step models conditional on whether the individual had made an attendance after 12-weeks, 6-months, and 1-year respectively, using the probit models from Table 28, shown previously. Therefore, only individuals who were still attending Slimming World classes in the time-period being reviewed were observed, with those who stopped attending being censored in the model. For example, when predicting weight-change at 6 months, only those who made an attendance in the period between the 3-months and 6-months after baseline were observed.

The model specification for the second step, the prediction of weight-change, featured the same explanatory variables as the first step, but again without join-type and total attendances. For the model predicting weight-change at 6-months, LOCF weight-change at 3 months was included as an explanatory variable to indicate each individual's ability to lose weight within the initial 12-week programme. However, for weight-change at 12-months and weight-change at 24-month, the predicted weight-change values from the Heckman models at 6-months and 12-months were used to predict 12-month and 24-month values for weight-change respectively.

Table 31, below, shows the regression output for the second step in the Heckman Correction model for weight-change predictions at 6-months, 12-months and 24-months. Again, target weight, full attendances and age were significant predictors of increased weight-loss, with the impact of full attendances becoming insignificant at 24-months. Interestingly, income quintiles did not have a significant effect on weight-change at any of the three time points, whilst being in a more deprived area in terms of education predicted significantly more weight-loss at 6 and 12-months.The selection output for each model is shown in Appendix 17, Appendix 18 and Appendix 19.

Table 31: Heckman Selection Model Predicting LOCF at 6, 12 and 24 Months with Attendance as the Selection Outcome (Appendix *20*)

Variable	Coefficient (6-Months)	t-statistic (6-Months)	Coefficient (12-Months)	t-statistic (1-Year)	Coefficient (24-Months)	t-statistic (2-Year)
Target Weight Change	0.0108***	15.52	0.0129***	16.30	0.0364***	10.86
Income IMD Quintile	-0.0127	-1.69	-0.00936	-0.49	-0.00919	-0.25
Diabetic	-0.0673*	-1.97	0.225**	2.72	0.203	1.34
Full Attendances	-0.122***	-48.79	-0.0733***	-9.31	-0.0110	-0.59
Education and Skills IMD Quintile	0.0181*	2.39	0.0457*	2.37	0.0292	0.79
Age at Start Date	-0.0179***	-40.85	-0.0184***	-16.15	-0.0139***	-5.92
Baseline Weight	-0.00306***	-8.02	-0.0248***	-25.34	-0.0490***	-25.10
Male	0.651***	24.31	1.192***	-	1.313***	-
LOCF Weight-Change 3 Months	1.419***	664.79	-	-	-	-
Heckman Weight-Change 6 Months	-	-	1.154***	296.68	-	-
Heckman Weight-Change 12 Months	-	-	-	-	0.920***	137.64
Constant	2.833***	64.36	4.812***	32.19	5.645***	14.24

N	393,318		393,318		393,318	

P<0.05*, p<0.01**, p<0.001***
*Selection output omitted

Table 32 illustrates LOCF weight-change and predicted LOCF weight-change at 6-months from the Heckman correction model in Table 31.
For the Heckman-correction model, as previously mentioned, only weight-change outcomes for individuals who continued attending Slimming World classes after the initial 12-week programme were observed. The table shows that predicted weight-change at 6-months is very similar to LOCF weight-change for those who continue attending the Slimming World programme.

However, as the Heckman correction model does not observe those who stop attending, and so therefore bases predictions of weight-change at 6 months on baseline characteristics and outcomes within the 12-week programme, the model's prediction of weight-change differs from the LOCF value. The model predicts more conservative weight-loss in comparison with the LOCF values. This may be a more realistic representation of weight-loss, as LOCF assumes that weight-change remains constant after a member of Slimming World leaves the programme, whereas the Heckman correction model considers the effect of not attending.

The issue with LOCF is that it assumes that participants have exactly the same measurement for weight-change as when they left the programme. When the goal of the intervention is behaviour change, using LOCF for dropout can exaggerate results, as it assumes that individuals have been able to maintain the weight-change that they were able to achieve when engaged with the programme (Kenward & Molenberghs, 2009). It could be that because these individuals leave before the initial 12-week programme is finished, they have not had enough exposure to the programme to be able to absorb enough information and develop strategies that would enable them to achieve further weight-loss and maintain weight-loss (Moroshko et al., 2011).

Therefore, this estimate appears to be plausible, as on average, those who leave before the initial 12-week programme is over are likely to have been disengaged with the programme and regain weight after leaving. However, the individuals who left the programme may have still received some benefit from attending the programme on average, and managed to maintain some of their weight-loss.

Table 32: LOCF and Projected Weight-Change at 6-Months (Appendix *21*)

Group	N	LOCF Weight-Change (kg)	Heckman Correction Predicted Weight-Change (kg)
Full Sample	393,318	-4.328 (4.718)	-3.994 (4.756)
Attended after 3 months (observed)	191,275	-6.925 (5.329)	-6.722 (4.755)
Last attendance before 3 months (unobserved)	202,043	-1.870 (2.006)	-1.411 (2.984)

*standard deviation in parentheses

Table 33 shows weight-change outcomes at 12-months. Again, when assessing the various weight-change outcome figures at 12-months, the Heckman correction model projects a more conservative weight-change for those who stop attending than the LOCF values, with those who left the programme within the first 12-weeks regaining much of their initial weight-loss. Those who attended past the initial 3-month period but left the programme before 6-months were shown to have continued to lose slightly more weight. This could be because these individuals completed the initial 12-week period and were engaged with the Slimming World programme. This means that many of them may have been able to maintain their habits over the next 6-months and some will have been able to continue to lose weight, although this weight-change was predicted to be less than for those individuals who continued attending past 6-months.

For those who continued attending past 6-months, the Heckman-correction model predicted 1.18kg less weight-loss than what was observed at the last observation of weight-change. This may be due to the small range of weight-loss predictions when compared with the LOCF weight-change values, as the Heckman-correction model does not predict extreme values as observed in the data. When comparing the median values, the LOCF data shows a value of 8.16kg compared with 7.79kg for the Heckman-correction predictions. It may be that the Slimming World members who have such a high weight-loss are outliers and therefore the Heckman-correction predictions are more representative of expected weight-change in a sample of Slimming World participants.

Across all groups, the Heckman-correction weight-change was just over 1kg less than the LOCF weight-change, which implies that Heckman-correction is again a more conservative estimate of weight-change.

Table 33: Heckman Correction Model Predicted Weight-Change at 12-months (Appendix *22*)

Group	N	LOCF Weight-Change (kg)	Heckman Correction Predicted Weight-Change
Full Sample	393,318	-4.532 (5.535)	-3.512 (5.848)
Attended after 6 months (observed)	107,767	-9.454 (7.470)	-8.279 (5.896)
Last attendance between 3 and 6 months (unobserved)	84,187	-4.606 (3.753)	-5.013 (5.181)
Last attendance before 3 months (unobserved)	201,364	-1.867 (2.003)	-0.333 (3.709)

*standard deviation in parentheses

When assessing the Heckman correction model weight-change projections at 24-months, shown in Table 34, those who left the programme in the first 12-weeks were predicted to have regained all but 0.06kg of their weight-change on average. Those who left the programme between 3 and 6 months were predicted to have regained 0.58kg of weight-loss when compared with the prediction at 12-months, but still maintained much of the weight-loss on average. At 24-months, weight-change was predicted to be only slightly lower than the LOCF value for those leaving between 3 and 6 months.

Members who left between 6-months and 12-months were predicted to have gained around 0.5kg on average after leaving. For those that continued attending after 12-months, the Heckman-correction model predicted a weight-loss 2.15kg lower than the LOCF value, which, similarly to the projection for those observed at 12-months, is likely due to extreme values in the LOCF weight-change variable.

Overall, the predictions made by the Heckman-correction models appear to be plausible, with the outcomes being intuitive at each time period. As well as this, the Heckman-correction predictions suggest a more conservative estimate of weight-change when compared with LOCF analysis.

Table 34: Heckman Correction Model Predicted Weight-Change at 24-months (Appendix *23*)

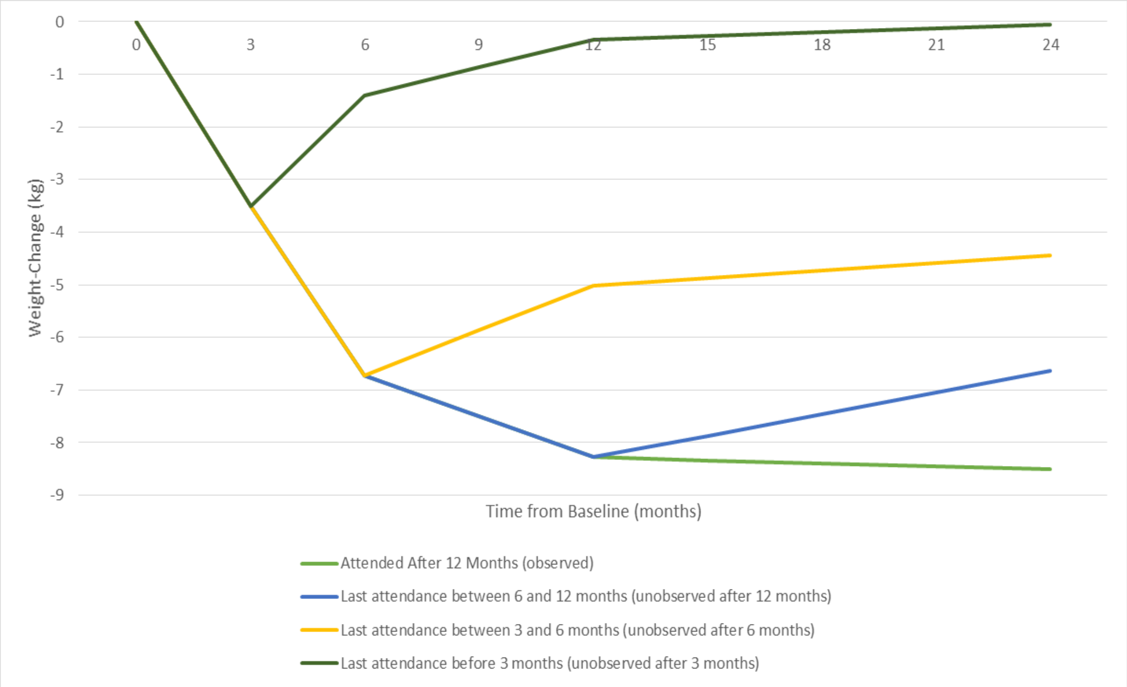
Group	N	LOCF Weight-Change (kg)	Heckman Correction Predicted Weight-Change
Full Sample	393,318	-4.387 (5.522)	-3.064 (5.912)
Attended After 12 Months (observed)	55,042	-10.644 (8.995)	-8.497 (6.211)
Last attendance between 6 and 12 months (unobserved)	53,523	-7.115 (5.682)	-6.632 (5.823)
Last attendance between 3 and 6 months (unobserved)	83,588	-4.587 (3.744)	-4.436 (5.298)
Last attendance before 3 months (unobserved)	201,165	-1.867 (2.003)	-0.057 (3.976)

*standard deviation in parentheses

**Last attendance before 3 months was lower when predicting weight-change at 24 months as some participants who dropped out in the first 3-months attended again after a year

Figure 15, below, illustrates weight-change over the 24 months following joining the Slimming World programme by group. It can be seen that at 3 months, all individuals made an attendance and so the mean weight-change of the full sample is shown. From here, those who continue attending continue to lose weight over the next 3-months, whilst those who leave the programme regain weight. Again, at 12-months, those who remain in the programme are predicted to lose more weight with those who leave regaining weight on average. The pattern continues at the final time-point at 24-months.

Figure 15: Heckman Correction Model Predicted Weight-Change over Time



5.4 Discussion

The purpose of this chapter was to identify proxy variables that could be used to model weight-change, and make predictions regarding weight-change for both those who remain in the Slimming World programme, and those who drop-out. By building regression models using proxy variables, this chapter has helped to provide evidence regarding the predictive ability of the theoretical framework of weight-management. The key findings from the chapter are as follows:

- Many variables in the Slimming World dataset were significant predictor of weight-change in the first 12-weeks
- Attendance was the most influential predictor of weight-change in the first 12-weeks, as well as continued attendance after 12-weeks
- The Heckman-correction model predicted less weight-loss on average for those that had left the programme compared with LOCF weight-change by accounting for the effect of attendance
- The Heckman-correction model predicted that even Slimming World members who left the programme in the first 12-weeks maintained some weight-loss on average at 24-months

Individual characteristics, join method, and attendance data were found to be significant predictors of future attendance, and weight-change, with predictions generally aligning with the hypotheses made by the theoretical framework. As the models were judged to have predictive power, the variables in the models were able to be used to make predictions of weight-change for those who were left the programme, and therefore were unobserved.

Using the Heckman-correction regression model has provided an alternative to using last-observation carried forward, or baseline-observation carried forward as a solution for missing data. Whilst LOCF and BOCF are very simplistic and do not consider any potential weight-change after leaving the programme, or assuming zero effect of the programme, the Heckman-correction has taken into account the effects of non-attendance in the latter stages of the 24-month period, alongside weight-change within the programme and individual characteristics to predict more intuitive estimations of weight-change. Therefore, by including non-attendance the Heckman-correction model assumes there is some benefit to attendance (unlike BOCF), but some regain when dropping out (unlike LOCF).

One limitation of the analysis is that proxy variables were required as not all characteristics in the theoretical framework were included in the Slimming World dataset. Therefore, some hypotheses may not have been proven by the regression analysis, but this may have been due to issues with the proxy variable not correctly reflecting the desired characteristic.

A limit of the predictions in this chapter is because weight-change outside of the Slimming World programme is unknown, the predictions made by the Heckman-correction model cannot be validated. The best method would be if follow-up of Slimming World members could be performed to validate these predictions, but in lieu of this the Heckman-correction predictions pass the face-validity test.

This chapter has been able to improve upon current assumptions regarding drop-out in weight-management programme by creating a regression model which is able to make individual level predictions. With prospective cohorts, data could be collected for purpose, and so remove the need for proxy variables. For example, future weight-management programme could collect data regarding income rather than using income IMD level, or include additional co-morbidities alongside diabetes.

These weight-change predictions at 1-year and 2-years will be used as measures of effectiveness for the case study when analysing the cost-effectiveness of the Slimming World programme. As well as this, to test the robustness of these predictions, sensitivity and scenario analysis will be performed on weight-change projections to test the impact of adjusting estimated values.

Chapter 6: Model-Based Economic Evaluations of Behavioural Weight-Management Interventions: A Systematic Review of Model-Based Evaluations with a Focus on Assumptions on Effectiveness

6.1 Introduction

The previous chapters of this PhD analysed data from the commercial weight-management programme Slimming World, and made predictions about effectiveness in the short-term to be used in cost-effectiveness modelling. To inform adaptations to a cost-effectiveness model, a review of how cost-effectiveness models have been applied to BWMs in the past was undertaken. The focus of the review was which models and assumptions have been employed, especially with regards to weight-trajectories following the BWM. The purpose of this review was to understand how previous analysts have modelled weight-management and the assumptions they have made regarding long-term effectiveness. This in turn would contribute toward the improvement of the current standard of cost-effectiveness modelling for behavioural weight-management programmes.

In public health interventions, economic evaluation is necessary for decision makers to optimise resource use. To make optimal decisions, economic evaluations must consider all relevant information, for the relevant course of time (Caro et al., 2012). As obesity is a condition which increases the risk of a number of diseases at all stages of life, costs and effects should be evaluated over the course of a lifetime (Masters et al., 2013). Weight-loss and long-term weight trajectories are therefore important factors in determining the effectiveness of an intervention. As trials and observational studies cannot feasibly track the costs and effects for each intervention or scenario over a lifetime, modelling methods must be employed to make estimations of these costs and effects (Ryder et al., 2009). Without modelling, decision makers may have insufficient evidence to reach an informed decision, and be underestimating the impact of weight-management interventions.
The aim of this chapter is to review how the long-term cost-effectiveness of BWMs had been modelled in previous evaluations, and what methods and assumptions had been used when considering weight-trajectories following the BWM. A recent systematic review, Griffiths et al., (2012), had the aim of

investigating economic evaluations of weight-management programmes. This chapter uses the papers identified by Griffiths et al. (2012), and a modified search strategy based on the strategy presented in Griffiths et al. (2012) to find papers that had modelled long-term costs and effects of BWMs since the final search performed in November 2010.

To address the aim of the chapter, multiple research questions were set out, listed below:

- How have papers modelled behavioural weight-management interventions in the past?
- What assumptions have economic evaluations made about weight-trajectories following programme completion?
- What effect does changing assumptions about weight-trajectories have on estimates of cost-effectiveness?

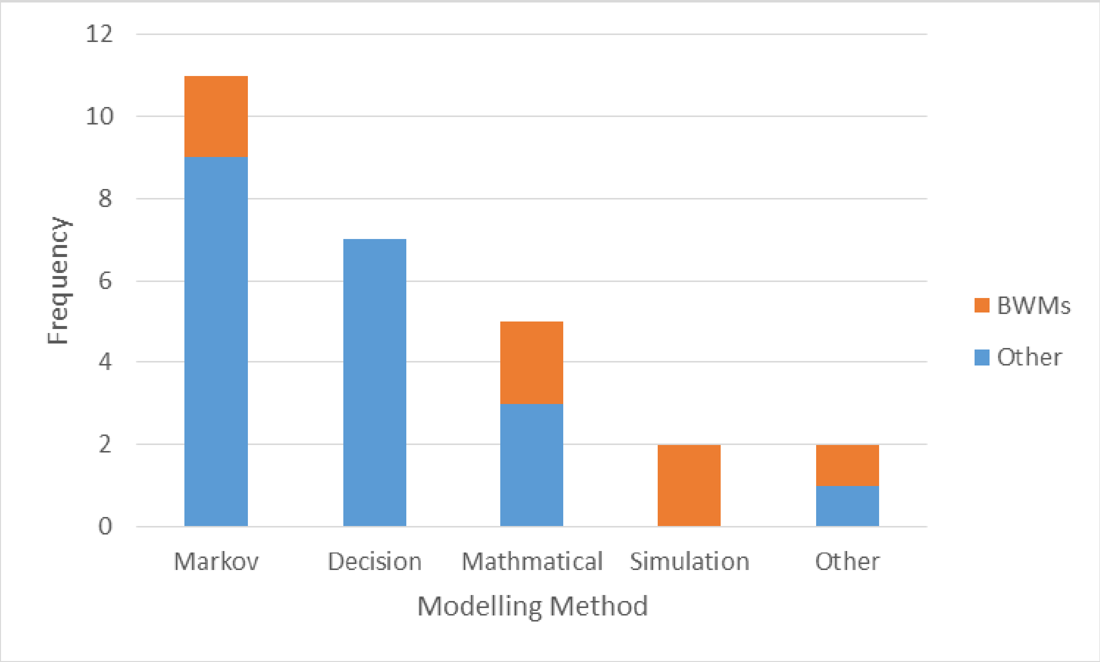
6.2 Background

The systematic review by Griffiths et al. (2012) aimed to review any intervention where weight-loss was the primary objective, and both the incremental costs and effects were presented. The programme identified 44 papers, with 27 of these papers including a consideration of future effects and costs. These were published between 1999 and 2012. The 17 papers included in the original Griffith’s et al. (2012) paper that did not employ modelling methods were not discussed as this update focusses on modelling methods and the assumptions made in modelling.

Griffiths et al. (2012) found that the most common co-morbidities being modelled were type 2 diabetes and cardiovascular diseases, which they recommended are included as minimum in economic evaluations in order to represent reality. By including more diseases that are associated with weight change, modelling studies will gain a more accurate estimation of the costs and effects of an intervention.

Figure 16 shows a histogram of the modelling choices in both BWMs and other interventions from Griffiths et al. (2012). Markov modelling was the most popular choice with 11 of the 27 papers employing this method, whilst only two used simulation modelling.

Figure 16: Modelling Methods Employed in the Griffiths et al. (2012) Review by Intervention Type



Of the 21 behavioural interventions included in the original review, only seven BWM evaluations modelled future effects. This was compared with 20 of 23 pharmaceutical and surgical trials using modelling methods. Griffiths et al. (2012) hypothesised this was due to cost-effectiveness evidence being required by reimbursement agencies. Of the seven BWM studies that employed modelling methods, two used Markov modelling, two used mathematical modelling and two used simulation modelling whilst one was unclear. Griffiths et al. (2012) highlighted that only Markov and simulation modelling are appropriate for modelling the future effects of weight management interventions due to their ability to model time and disease complications, and that despite this, the majority of papers continue to employ alternative methods.

Griffiths et al. (2012) stated a well-designed model should be able to incorporate extensive sensitivity analyses by altering parameter values. These parameter values should come from primary data in RCTs with sensitivity analysis using ranges defined by realistic extremes. A limitation noted by Griffiths et al. (2012) was that instead of including co-morbidities, often a direct relationship between BMI and mortality was used. This limits the extent to which sensitivity analysis can be performed. Models should then be validated internally and externally to minimise bias, with few studies meeting this requirement.

6.3 Methods

6.3.1 Search strategy

The search strategy was created by modifying the original search strategy in Griffiths et al. (2012) in line with the aim of this study. To make the search more appropriate for identifying cost-effectiveness modelling studies, new search terms were identified from preliminary searches of Medline in the categories of ‘obesity’, ‘cost-effectiveness’ and ‘diet’. As well as this to ensure papers focussed on modelling methods, a new category for search terms – ‘model’, was included. Table 35 shows the modified search strategy where each column was combined by the operator ‘OR’ and each row was combined by the operator ‘AND’.

To test how effective the strategy was, the search terms were used to identify the papers included in Griffiths et al. (2012). The modified search strategy was able to identify 26 of the 27 modelling papers (96.3%) included in Griffiths et al. (2012), and all 7 of the 7 papers that modelled BWMs. As the 26 papers were all identified in a search of OVID Medline, Embase and PsychINFO, these three databases were used to update the review. The search strategy removed results that did not focus on adults, did not focus on humans, and were not published in English.

Table 35: Search Terms

Obesity	**Cost-effectiveness**	**Diet**	**Model**
Overweight	Cost-utility analysis	Exercise	Simulation
Hyperphagia		Lifestyle	Markov
Overeating		Bariatric surgery	Mathematical
		Gastric band	Quality-adjusted-life-years
		Weight-loss	Sensitivity-analysis
		Drug	

After performing the search in Table 35 to test whether the modelling papers included in Griffiths et al. (2012) were able to be identified, the search was then further refined to focus on economic evaluations of BWMs, as lifestyle programmes were the focus of this update, whilst Griffiths et al. (2012) focussed on all weight-management interventions. The search was refined by using the ‘NOT’ operator for the terms ‘bariatric surgery’, ‘gastric band’ and ‘drug’. This was to improve the efficiency of the search as less inappropriate papers would be identified by the search.

If any reviews were identified, the included papers were searched to identify any modelling papers that fir the inclusion and exclusion criteria. Grey literature was included if it matched the criteria in the search strategy.

The final search in Griffiths et al. (2012) was run in November 2010 and so this updated search was limited to papers published from 2010 to the current date (27/07/2018), so the update would focus on papers published after the final Griffiths et al. (2012) search. As searches within OVID can only be limited by year, the search contained all articles published in 2010. However, only papers published in November or December of 2010 were considered.

Following the search, a second reviewer checked 20% of the titles and abstracts to ensure that there was consistency in which papers were included in the review, and that both reviewers were including the same papers based on the inclusion and exclusion criteria. Where there was a disagreement between reviewers on any papers, the reasons for including and not including the paper were discussed, and an attempt was made to agree upon whether each paper would be included. If an agreement could not be reached following discussion, a third party arbitrated. Following this, each of the papers that were selected to be included in the review were checked by the second reviewer, and again, any disagreements were discussed until an agreement was made.

6.3.2 Inclusion and Exclusion Criteria

The review inclusion and exclusion criteria were taken from the original Griffiths et al. (2012) paper, but again, with modifications to fit the aims of this update. The inclusion criteria were as follows:

- The paper must report on a BWM.
- Weight-change must be the primary study objective.
- The study must use modelling methods to combine costs and effects into a form of cost-effectiveness, cost-utility or cost-benefit analysis.
- The programme must be for adults (age 16+).

Exclusion criteria were:

- The intervention involved surgery, pharmacotherapy or meal replacements.
- Any papers not in English language.
- If participants had a pre-existing condition that was the focus of the intervention.

The inclusion and exclusion criteria were set to ensure the focus remained on economic evaluations of BMWs with the primary aim of weight-change. Interventions with surgery, pharmacotherapy or meal replacements were excluded as the focus of these interventions was not behavioural change. Papers that focussed on samples of individuals with pre-existing conditions were also excluded as this review is interested in a general population, and having a pre-existing condition may affect weight-change outcomes.

6.3.3 Data Extraction

Data from the BWM papers that used economic modelling in the Griffiths et al. (2012) review and the papers identified in the modified search were extracted using a bespoke data extraction form, with the aim of capturing a number of pieces of information. The first was what the intervention compromised of and the service offered to participants. The methods used in modelling in each paper were also extracted. The long-term assumptions made by each model about weight trajectories and the source of these trajectories were noted. The cost-effectiveness and the effect of sensitivity analysis on long-term effectiveness for each intervention were also recorded.

The data extracted from each of the papers were combined in a narrative synthesis. Since the aim of the review was to identify methods, choices and assumptions by modellers, rather than evaluate the cost-effectiveness of BWM interventions, no qualitative evidence synthesis was attempted. However, descriptive statistics were presented. Data regarding the BWMs and the study sample was synthesised first to understand what each intervention entailed. Following this, the modelling methods and the assumptions made about weight-trajectories were presented. The last data to be synthesised were the estimates of cost-effectiveness and the effect of adjusting the assumptions regarding weight-trajectories on these estimates.

For cost-effectiveness measures, net benefit was calculated where possible. This was done using the formula in Equation 32, with the thresholds used being £20,000 per QALY as used by NICE (Paulden, 2017). Where currencies were not reported in British Sterling, the following conversion rates were taken on the 22nd September 2018 from Morningstar (2018) and used: £1 = 4.55NIS, 1.30USD, 1.14EUR, 1.82AUD, 1.30CHF. Where a range of costs or benefits was reported, a mean value of the two was used.

Equation 32

$$Net\ Benefit = (Incremental\ QALYs * Threshold) - Incremental\ Cost$$

6.3.4 Quality Assessment

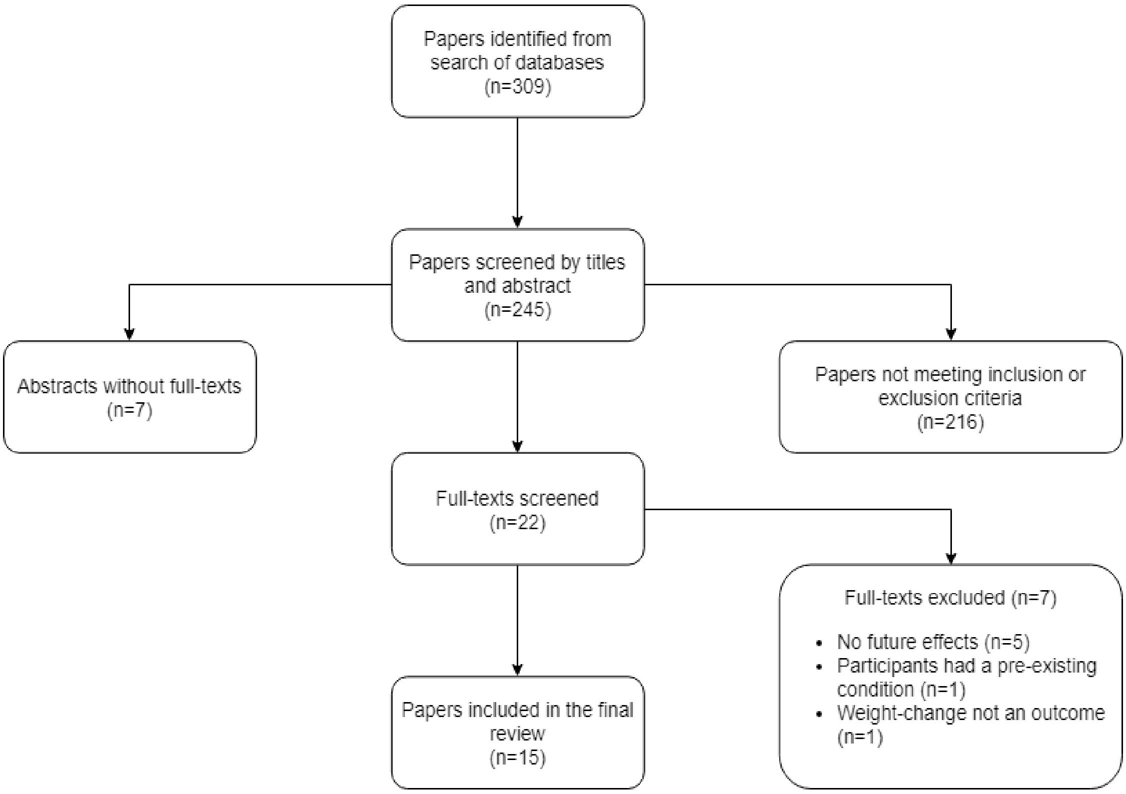
Papers that were included were then subjected to a comprehensive quality assessment, using the Phillips checklist, which is a checklist designed specifically for the purpose of assessing the quality of modelling studies (Phillips et al., 2006). After papers were identified and included in the review, the checklist was completed for each study in turn. Responses to the checklist included ‘Y’ for yes, ‘N’ for no, ‘U’ for unclear and ‘NA’ for not applicable.

6.4 Results

6.4.1 Search Results

The search of the three databases returned 245 unique results. Of the 245 titles and abstracts reviewed, 22 that had full-texts available met the inclusion criteria and were selected. Seven papers were dropped after reading the full-texts as it was found they either did not consider future effects, participants had a pre-existing condition, or weight-change was not reported. Fifteen full-texts published since the original review's final search were included in this update. Figure 17 shows a summary of the search process.

Figure 17: A PRISMA Diagram for the Search Strategy



6.4.2 Characteristics of the Studies

The seven papers taken from Griffiths et al. (2012) and the 15 studies identified by the search strategy modelled various interventions. A summary of each of the interventions across the 22 papers is shown in Table 36. The table shows a summary of the sample of participants in each study, the length of each of the programmes, and a brief description of what the programme entailed. The seven papers published in 2010 and before were taken from

Griffiths et al. (2012), while the 15 papers published after 2010 were identified by the search strategy described in this chapter.

Table 36: The Behavioural Weight-Management Programmes Modelled

Paper	Study Sample	Programme Length	Study Design and Programme Description
Gray et al. (2018)	UK men aged 35-65	1-year	Participants offered a weight-management programme encouraging physical activity and diet change
Thomas et al. (2017)	UK adults with a high risk of type 2 diabetes taken from HSE	Unclear	Diabetes prevention intervention focusing on lifestyle change – applied a weight-loss from a meta-analysis of interventions
Michaud et al. (2017)	US overweight and obese adults	1-year	Community weight-loss programme
Zomer et al. (2017)	UK individuals that were overweight or obese taken from the HSE aged 30-74 free of CVD	1-year	Hypothetical weight-loss applied to HSE data
Ahern et al. (2017)	UK adults with a BMI of 28kg/m^2 or higher	1-year	A community weight-management programme (12-weeks or 52-weeks)
Smith et al. (2016)	US individuals that were overweight or obese	1-year	Online lifestyle programme for diabetes prevention

Haussler and Breyer (2016)	German individuals with obesity	1-year	Lifestyle intervention for obesity reduction
Hoerger et al. (2015)	US individuals with obesity and covered by Medicare	6-months with a view for extension if successful	Intensive behavioural therapy for obesity – hypothesised weight-change
Wilson et al. (2015)	Mexican-origin individuals	12-weeks	Community-based lifestyle intervention to reduce diabetes risk
Fuller et al. (2014)	Australian, UK and German overweight and obese adults	1-year	Community weight-management programme or GP advice
Lewis et al. (2014)	UK adults with obesity	3-years	Weight-management lifestyle programme
Meads et al. (2014)	UK adults	1-year	Primary care referral to a community weight-management programme
Ginsberg and Rosenberg (2012)	Israeli population	Not discussed	Applied the effects of various weight-management programmes at a population level
Miners et al. (2012)	UK individuals with obesity	1-year	E-learning devices with a meta-analysis of RCT data informing effects
Forster et al. (2011)	Australian population that were overweight or obese	6-months and 1-year	Applied the effect of a low-fat diet and diet and exercise programme at a population level
Cobiac et al. (2010)	Two programmes: Australian individuals with a desire to improve diet, exercise and/or weight UK individuals aged 18-65 with BMI 27kg/m^2 to 40kg/m^2	2-months for the weight-management programme 6-months for the commercial weight-loss programme	A weight-management programme, 'Lighten Up', for promoting healthy lifestyle changes in diet and activity with behavioural support A commercial weight-loss programme, 'Weight Watchers', with focus on a

			low-calorie diet and advice on physical activity
Trueman et al. (2010)	UK individuals with a BMI of 30kg/m^2 or higher, or 28kg/m^2 with comorbidities	2-years	Advisors providing advice regarding weight-management, improving diet and behavoural change
Gustafson et al. (2009)	US women with low-income aged 40-64 and a BMI of 25kg/m^2-45kg/m^2	16-weeks	Weekly group sessions delivered by a health counsellor about healthy eating, physical activity, and behaviour change
Bemelmans et al. (2008)	Dutch general population aged 20-80 Overweight Dutch adults aged 30-80 with a moderate risk of diabetes	5-years for community intervention 3-years for health care intervention	Community intervention with focus on nutrition and exercise Health care intervention with focus on diet and exercise in a health care setting
Galani et al. (2007)	Swiss simulated population of individuals with overweight or obesity	3-years	Lifestyle intervention consisting of group dietician sessions and supervised exercise sessions
Roux et al. (2006)	US hypothetical cohort of 35-year old women with BMI of 25kg/m^2 or higher, and no hypertension, type 2 diabetes, or hypercholesterolemia	1-year	A dietary weight-loss intervention with a 6-month weight-loss phase and 6-month maintenance phase A diet and pharmacotherapy intervention
Olsen et al. (2005)	Danish GP attendees with a BMI of 30kg/m^2 or higher, large waist circumference, dyslipidemia or type 2 diabetes	1-year	Dietician counselling with advice on healthy eating and physical activity

Papers focused on programmes offering diet, physical activity, and behavioural support to individuals that were overweight or obese. Four of the 22 papers included interventions that lasted over 1-year in duration. The types of programmes being modelled included community weight-management programmes, advice from healthcare professionals, online help and e-devices, and diet programmes, as well as some studies applying hypothetical weight-loss to survey data. Ten of the 22 papers included samples from the UK population.

6.4.3 Modelling Methodologies and Weight-Trajectory Assumptions

A range of modelling methods were employed across the 7 studies included from the Griffiths et al. (2012) and the 15 studies identified by this review, shown in Table 37, below, alongside a summary of the assumptions made in modelling regarding long-term weight trajectories, the evidence the assumptions were based on, and time-horizons considered.

Table 37: Modelling Methods and Weight-Trajectory Assumptions

Paper	Model Type	Weight-regain Type	Weight-regain Assumption	Weight-regain Assumption Justification*	Control Group*	Post-programme Weight Regain End Point	Time-horizon
Gray et al. (2018)	Markov	Follow-up at 3.5 years	No regain assumption made after 3.5 years, then unclear assumptions regarding weight-trajectory	N/A	‘No intervention’ group were weighed at 12-months, then applied an average population trajectory of 0.46kg per year from 12-months to 3.5 years. This was using the European Prospective Investigation into Cancer and Nutrition study (Freisling et al., 2016). Five alternative hypothetical control scenarios were also included	3.5 years	Lifetime
Thomas et al. (2017)	Patient-Level Simulation Model	Linear regain - fixed time	Regain to match non-intervention metabolic trajectory after 5 years	Regain according to assumptions used for NICE guidelines regarding diabetes prevention (Gillett et al., 2011)	Alternative simulation with individuals being given no intervention	Lifetime	20-years

				Unclear assumptions made about non-intervention metabolic trajectory			
Michaud et al. (2017)	Markov	Probabilities for weight-change each year	Annual transition probabilities depending on initial weight change and individual characteristics which stayed constant over time	Annual transition probabilities taken from an evaluation of a community weight-loss programme (Estabrooks et al., 2017)	Compared with no intervention simulation applied to same individuals – unclear weight trajectories for no intervention group	Lifetime	Lifetime
Zomer et al. (2017)	Markov	No regain	No regain	N/A	N/A	No regain	10-years
Ahern et al. (2017)	Patient-level Simulation Model	Linear regain - fixed time	24-month follow-up then regain to baseline between years 2 and 5 after then followed national weight trends	No source for assumption regarding regain to baseline between 2 and 5 years National weight trends from the HSE (HSE, 2016)	Same as the intervention group assumptions	5-years and lifetime	25-years

Smith et al. (2016)	Markov	Probabilities of weight-change were applied to participants at a 12-month follow-up, but no weight-change assumptions after the 12-month follow-up	No regain.	N/A	Usual care – applied a probability of various weight-change levels at 12-months	No regain	10-years
Haussler and Breyer (2016)	Markov	Follow-up then linear regain of diabetes risk - fixed time	4-year follow-up then linear adjustment to match control group diabetes risk after follow-up over 10 years	Assumption based on findings regarding long-term effects of weight-reduction (Diabetes Prevention Programme Research Group, 2009; Norris et al., 2005)	Artificial control group formed from German panel data and used their recorded weight trajectories	14-years	20-years
Hoerger et al. (2015)	Markov	Linear regain - fixed amount	Regain 0.3 units of BMI per year until baseline	According to a meta-analysis of dietary counselling for weight-loss (Dansinger et al., 2007). Unclear weight-trajectory after regain.	Usual care with constant weight throughout	Until baseline reached	Lifetime (or when patient reaches 95 years)

Wilson et al. (2015)	Continuous Markov model	No weight-regain assumption made. Projected weight-loss based on SSB consumption	Follow-up of participants at 3-years and projected weight loss at 3-years based on SSB consumption. No reference to assumptions about weight-trajectories after 3-years	Methods for projecting weight-loss using SSB consumption from Wang et al. (2012)	Simulated control group with matching characteristics. Unclear weight-trajectory	No regain	20-years
Fuller et al. (2014)	Markov	Probability of weight-regain between 12-months and 24-months, then linear regain	Average re-gain of 0.09kg/m^2 per month. After 2 years, individuals gained 0.03 BMI points per month from the end of follow-up until weight is regained. Unclear trajectory after baseline weight is met	Weight regain probabilities taken from trial data. Weight trajectories after 2 years taken from Dansinger et al. (2007)	Standard care - probability of weight-regain between 12-months and 24-months average of 0.03kg/m^2 per month with baseline weight being met around 4-years post-intervention	Until baseline (met at approximately 5 years post-intervention)	Lifetime
Lewis et al. (2014)	Mathematical	Follow-up then linear-regain - fixed amount	Regain 1.87kg/m^2 per year until background rate is met then 0.16kg/m^2 per year	Initial regain taken from trial data. Background rate taken from Ara et al. (2012) as the background natural annual change in BMI	No treatment group who were applied the background annual rate of 0.16kg/m^2 growth per annum	Until background rate and lifetime	10-years

Meads et al. (2014)	Markov	Linear regain - fixed amount	Linear regain of 0.429kg per year	Regain rate taken from Ara et al. (2012)	Usual care group which had a fixed weight from baseline to 12-months then a linear regain of 0.429kg per year	Lifetime	Lifetime
Ginsberg and Rosenberg (2012)	Mathem atical	Non-linear regain for effect of intervention	50% of effect of intervention decrease each year	Recidivism rate was based on a number of studies (Franz et al., 2007; Knowler et al., 2002; Wing and Phelan, 2005; McGuire et al., 1999a; McGuire et al., 1999b)	No control group and no assumptions regarding weight-gain of population without an intervention	Lifetime	Lifetime
Miners et al. (2012)	Discrete Event Simulati on	Linear regain - fixed amount	Regain 1kg per year – converted into BMI for men and women based on average height	Figure of 1kg per year taken from Fine et al. (1999) and Heitmann and Garby (1999)	Conventional care in which individuals gain 1kg per year following treatment cessation	Lifetime	Lifetime
Forster et al. (2011)	Markov	Linear regain – fixed amount	Gain 0.03 BMI points per month from the end of intervention for 5.5 years. No weight-loss remained indefinitely. Unclear what assumptions are made after 5.5	Assumption taken from a meta-regression on diet and exercise programmes (Dansinger et al., 2007)	Synthetic control groups which experienced only weight-change from the general BMI trend (Haby and Marwick, 2008)	5.5 years	Lifetime

			years post-intervention				
Cobiac et al. (2010)	Unclear	Non-linear decay of effect	Decay of intervention effect of 50% per year	Found in a meta-regression weight lost was regained after 5.5 years (Dansinger et al., 2007)	Used average change in BMI between 1999/2000 and 2004/05 as a background weight trajectory for Lighten Up, not discussed for Weight-watchers (Dunstan et al., 2001; Barr et al., 2006)	Indefinite	Lifetime
Trueman et al. (2010)	Patient Simulation	Linear regain to match no-intervention followed by background trajectory weight-change	12-month weight-loss regained over the next 2-years then a background weight-gain of 1-kg per year	24-month outcomes from Counterweight Project Team (2010). No evidence provided for assumptions regarding further weight-gain	Simulated population of the UK applied a weight-trajectory representing annual UK weight-gain (1kg per year)	2-years of regain, indefinite background trajectory	Lifetime

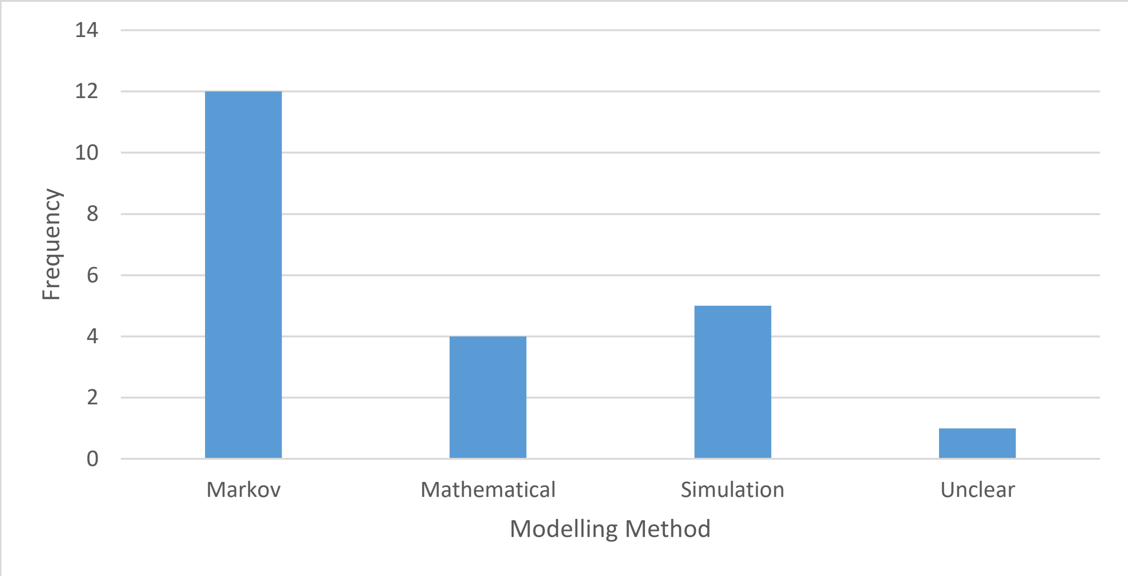
Gustafson et al. (2009)	Mathematical	No regain	No regain	N/A	Control intervention	No regain	30.4 years (Life expectancy for average member)
Bemelmans et al. (2008)	Markov	No-regain. Change in transition rates between BMI categories reverted to pre-intervention level	Change in transition rates between BMI categories reverted to pre-intervention level – sustained effect of programme compared with reference case	The 5-year change in transition rates was based on the intervention results. The basis for the sustained effect is unclear	Parameters of the model applied to the same hypothetical cohort and are unchanged throughout the time-horizon	Permanent effect of programme	Lifetime
Galani et al. (2007)	Markov	Linear weight regain.	Weight-loss maintained to 6-years then a linear re-gain to baseline over the next 4-years	Assumptions based on data found in observational trials (NICE, 2006)	Standard care, no regain assumptions stated	10-years	Lifetime
Roux et al. (2006)	Patient Simulation	Probability of weight-loss maintenance	Participants were applied a probability of achieving 10% weight loss at 6-months, and then a probability of maintaining that weight-loss at 1 and	Weight-maintenance probabilities from small body of literature regarding weight-loss maintenance (Lowe et al., 2001; Anderson et al.,	Routine care – applied a smaller probability of weight-loss at 6-months, and a probability of maintaining that weight-loss	Regain according to probabilities at 6-months/1-year and 5-years then	Lifetime

			5 years – those who maintain at 5 years maintain indefinitely, those who do not regain to baseline instantly	1999; Gosselin and Cote, 2001; McGuire et al., 1999b; Anderson et al., 2001). Longer-term maintenance rates from the National Weight-Control Registry (Wing and Hill, 2001)		weight stays constant.	
Olsen et al. (2005)	Mathem atical	No regain	Change in probability of death is maintained indefinitely	N/A	GP advice	No regain	Lifetime (participant s expected to reach 80)

*All references in the 'weight-regain assumption justification' and 'control group' columns were cited in the corresponding paper in the 'paper' column

Figure 18 shows a histogram of the modelling methods employed across the 22 papers. Markov modelling was the most commonly used model design, whilst 5 papers used simulation models and 4 relied on mathematical equations.

Figure 18: Modelling Method Employed



Fourteen of the 22 (64%) studies considered a lifetime time-horizon. The remaining 8 studies used time-horizons ranging from 10-years to 30.4-years[4] with a mean horizon of 18.18 years.

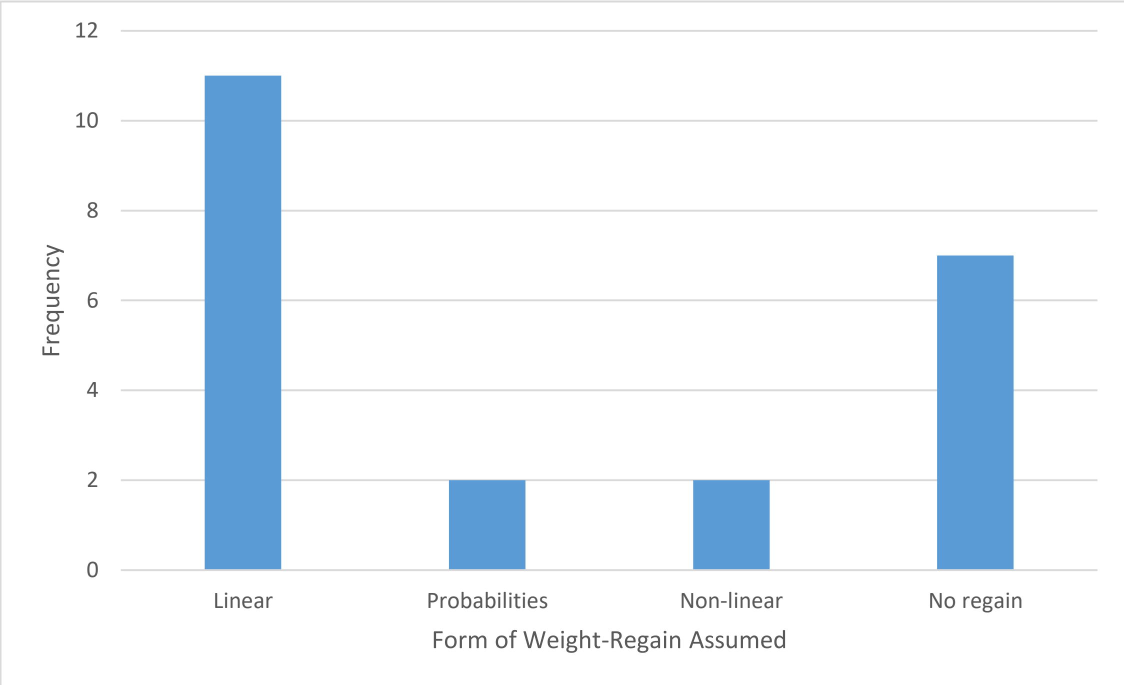
Of the 22 papers included in the review, 15 (68%) made assumptions about weight-regain following the end of the study period. Whilst Gustafson et al. (2009) and Bemelmans et al. (2008) did not make any assumptions about weight regain in the base-case, they tested alternative scenarios in which intervention effects were not sustained. Gray et al. (2018) and Wilson et al. (2015) followed-up participants at 3.5 and 3 years respectively, but did not make any assumptions about further weight-change after follow-up.

Linear regain following programme completion was the most common assumption made, illustrated in Figure 19, with 11 of the 22 papers making this assumption. Two papers used probabilities of weight-regain with Michaud et al. (2017) assigning probabilities to different rates of weight-change, and Roux et al. (2006) using probability chances of weight-loss maintenance at various

[4] The time-horizon of 30.4 years was chosen to match the mean life-expectancy of the average participant

time-points. Ginsberg and Rosenberg (2012) and Cobiac et al. (2010) both made the assumption that weight-regain was non-linear, with intervention effectiveness decaying by 50% each year. The remaining 7 papers assumed that the effect of the BWM intervention was permanent and sustained in the long-term. Fourteen of the 15 papers based these assumptions on literature including trial data, meta-analyses, and recommendations from a governing body.

Figure 19: Weight-Regain Assumptions Made



The papers that modelled weight-regain made a range of assumptions about weight-regain end-points. Four of the 15 studies assumed that participants regained weight to reach baseline, with another 4 papers assuming that participants regained weight until they matched the non-intervention background weight trajectory. Six of the studies assumed a fixed amount of regain or fixed probabilities of weight-regain for a certain time-period (2-10 years). The final study, Roux et al. (2006), assumed a percentage of individuals maintained their weight-loss at specified time-points.

A total of 8 papers included a consideration of a background weight-trajectory that individuals joined in the long-term. The remainder either assumed a constant weight in the long-term, or did not make their assumption clear. Six of these 8 papers cited the evidence used to produce the assumption.

Twenty-one of the 22 papers used control groups in their analysis, with the exception being Ginsberg and Rosenberg (2012) who used a cost-effectiveness model to apply the effects of a group of weight-loss programmes to the population of Israel. The most common assumption made by papers was a hypothetical control group with matching baseline characteristics, or individuals taken from panel data, which were applied a rate of annual weight-gain.

Sensitivity analyses were employed on weight-regain assumptions in 9 of the 22 papers (41%). Four of the papers tested two-way sensitivity analyses. Cobiac et al. (2010) varied the decay of effect from 0% to 100% per year, whilst Roux et al. (2006) varied the probability of weight-loss maintenance at 1-year and 5-years. Hoerger et al. (2015) tested scenarios of faster weight re-gain and no re-gain, although in the no-regain scenario, maintenance costs were also assumed to continue. Ginsberg and Rosenberg (2012) adjusted the decay of effect from 50% in the base-case, to 20% and 80% per annum.

Three papers tested more conservative estimates of weight-regain. Meads et al. (2014) tested two alternative conservative assumptions where all weight-loss was regained within 2 and 3 years. Similarly, Thomas et al. (2017) used an alternative scenario where the weight-trajectory matched the no-intervention group in 3 years rather than the 5 assumed in the base-case. Whilst Gustafson et al. (2009) assumed permanent effects of the intervention in the base-case, weight-regain assumptions were tested in scenario analysis. Gustafson et al. (2009) tested the assumptions of regaining half of weight-loss and regaining all weight-loss after 1-year.

Two papers tested only more optimistic scenarios. Trueman et al. (2010) tested a scenario in which the weight trajectory was returned to the background trajectory rate after 12-months rather than all weight being regained to match the control group, meaning the intervention effect was sustained over the control group for the model time horizon. Forester et al. (2011) analysed the effect of halving the rate of weight-regain.

Miners et al. (2012) also considered an alternative scenario in which the time taken to gain 0.1 BMI points was doubled. However, Miners et al. (2012) also doubled the amount of time taken to gain 0.1 BMI points in the conventional care group, and so this alternative scenario was not a true test of altering the weight-regain assumption in the intervention group.

6.4.4 Reported Outcomes and Robustness to Adjusting Weight-Trajectory Assumptions

Table 38 shows a summary of the cost-effectiveness results reported by each study. When reviewing the outcomes reported in the 22 papers, 15 papers reported QALYs as an effectiveness measure. Two papers reported disability-adjusted-life-years (DALYs), with 2 papers using life-years gained as their measure of effectiveness. Zomer et al. (2017) assessed the thresholds a hypothetical intervention would be cost-effective at. Two papers did not quote measures of effectiveness but stated that the programmes reviewed were cost-saving. A total of 18 included programmes were found to be cost-effective, with 7 of these being cost-saving in the long-term.

For the 15 papers that reported QALYs gained, net benefit was calculated at both the £20,000 and £30,000 per QALY thresholds. Thirteen interventions were found to be cost-effective at both thresholds, with neither Miners et al. (2012) or Wilson et al. (2015) finding their programmes to be cost-effective at the required threshold. The mean net benefit across the 15 studies was £1,651 at the £20,000 per QALY threshold and £3,188 at the £30,000 per QALY threshold.

Table 38: Cost-Effectiveness Results

Paper	Incremental Costs	Incremental Benefits	Cost-Effectiveness Reported Results	Net Benefit
Gray et al. (2018)	£1450-£1680 per participant	0.679-0.821 QALYs per person	£1790-£2200 per QALY against hypothetical scenarios for control groups	£13,435
Thomas et al. (2017)	-£75 per participant	0.03552 QALYs per person	Dominant over no intervention (-£2120 per QALY)	£785
Michaud et al. (2017)	Not stated	Not stated	Return on investment of $16.7 for every $1 invested	N/A
Zomer et al. (2017)	Not stated	Not stated	Interventions should cost <£34/<£51 to be cost-effective at £20,000/£30,000 cost-per QALY	N/A
Ahern et al. (2017)	£46 per person	0.01925 QALYs gained vs control	£2,394 per QALY vs the control group	£339
Smith et al. (2016)	$591 per participant	0.0412 QALYs per person	$14,351 per QALY	£369
Haussler and Breyer (2016)	Not stated	Not stated	Cost saving of €327 per year	N/A
Hoerger et al. (2015)	-$24	0.0542 QALYs per person	Dominant	£1,102
Wilson et al. (2015)	Total of $5,972,720 for 2%, $6,127,407 for 5%	104 QALYs for 2% weight-loss goal and 99 QALYs for 5% weight-loss goal	$57,430 per QALY for 2% weight-loss scenario and $61,893 per QALY for 5% weight-loss scenario	-£7,519 for 2%, -£8,173 for 5%**
Fuller et al. (2014)	-70AUD per participant	0.03 QALYSs per person	Cost-saving (-6,225 AUD per QALY)	£639
Lewis et al. (2014)	£1,613 per participant	0.128 QALYs per person	£12,585 per QALY vs no treatment	£947
Meads et al. (2014)	-£924 per person	0.22 QALYs per person	Dominant over usual care	£5,324

Ginsberg and Rosenberg (2012)	1.55billion NIS	32,671 QALYs for the population of Israel	47,559 NIS per QALY	£68***
Miners et al. (2012)	£762 per person	0.007 QALYs per person	£102,112 per QALY	-£622
Forster et al. (2011)	446AUD for diet and exercise, 187AUD for low-fat diet per person	5,900 DALYs for diet and exercise, 2,900 for low-fat diet per person	12,000 AUD per DALY for diet and exercise programme, 13,000 AUD per DALY for low-fat diet	N/A
Cobiac et al. (2010)	At a population level, AUD5.3m for Lighten Up / AUD8.3m for Weight Watchers	38 DALYs for Lighten Up, 54 DALYs for Weight Watchers	130,000 AUD per DALY for Lighten Up (dominated) / 140,000 AUD per DALY for Weight Watchers (dominated)	N/A
Trueman et al. (2010)	-£27 per person	0.06 QALYs gained	-£473 (dominant)	£1,227
Gustafson et al. (2009)	$242 per participant	0.13 life years gained	$1,862 per life year gained	N/A
Bemelmans et al. (2008)	€6,954,000,000	1,220,000 QALYs saved	€5,700 per QALY for combined implementation of interventions	£1,378***
Galani et al. (2007)*	285CHF per person	0.2538 QALYs	1284CHF per QALY	£4,857
Roux et al. (2006)	$3,080 per person	0.243 QALYs	$12,640 per QALY	£2,488
Olsen et al. (2005)	1,293DKK per person	0.0528 life years gained	23,481DKK per life year gained	N/A

*Figures were taken as the mean across all subgroups as overall figures were not reported
**Net benefit was calculated using the sample of 335 members
***Net benefit was calculated using the population quoted in the study

All 9 papers that performed sensitivity analysis on weight-regain assumptions reported the effect on cost-effectiveness. Cobiac et al. (2010) found from two-way sensitivity analysis that increasing BMI regain by 0.01units per month increased ICER values by 3%. Roux et al. (2006) adjusted the percentage chance of both 1-year weight-loss maintenance and 5-year weight-loss maintenance, and found a large effect on cost-per-QALY estimates, with an increase in the chance of long-term weight-maintenance from 20% to 40% halving the cost-effectiveness ratio estimate, and a fall in the long-term maintenance rate to 0% more than doubling the ICER. The effect of a reduction in the percentage chance of maintenance was shown to have a larger impact than increasing the likelihood of maintenance.

Hoerger et al. (2015) also performed two-way sensitivity analysis on the effects of a fully-effective programme. Hoerger et al. (2015) found the programme was cost-saving in the long-term with the base-case assumptions, but the cost per QALY was $2,604 when a faster regain was assumed. The cost per QALY for the permanent weight-loss, but continuing maintenance costs was $28,896 per QALY. The base-case provided an additional 0.0422 QALYs, which fell to 0.0403 QALYs for the faster regain scenario, and rose to 0.0786 for the permanent weight-loss scenario. In Ginsberg and Rosenberg's (2012) study, reducing the decay of effect from 50% to 35% and 20% reduced costs per QALY from 47,559 to 29,661 NIS and 11,812 NIS respectively. Increasing the recidivism rates to 65% and 85% increased costs per QALY to 65,475 NIS and 83,355 NIS.

Meads et al. (2014) focussed on testing more conservative assumptions. The programme remained dominant against usual care when assuming that all weight was regained in 3-years and 2-years. However, the cost savings fell from £924 per person to £301 and £165 respectively. Incremental QALYs gained fell from 0.22 in the base-case to 0.07 with the 3-year regain assumption and 0.04 in the 2-year regain scenario. Thomas et al. (2017) also tested a more conservative scenario by assuming all weight was regained in 3-years rather than 5. This led to the programme no longer being cost-saving for those with a BMI of under 35kg/m^2. Gustafson et al. (2009) found that by regaining half of the weight-lost after one year, the number of QALYs saved fell from 0.13 to 0.067, and to 0.013 if it was assumed that all weight-loss was regained after a year. This caused the cost-per-QALY figures to rise from

$1,862 per QALY to $3,612 and $18,615 per QALY in the half of weight regained and all of weight regained scenarios respectively.
In the base case in Trueman et al. (2010), the assumption was made that participants regain weight to match the no intervention group 2 years from programme completion. An alternative scenario was also considered, where instead of following this pattern, at the programme completion participants gain weight at the natural trajectory, and so maintain their weight-loss over the no-intervention group. In this scenario, the incremental cost fell from –£27 per person to -£80, whilst the incremental QALYs gained increased from 0.06 to 0.09, which again was dominant over no intervention. Forster et al. (2011) found that by halving the rate of weight regain, the cost per DALY for the diet and exercise programme fell from 12,000AUD to 620AUD and the cost per DALY for the low-fat diet fell from 13,000AUD to 3,000AUD.

6.4.5 Quality Assessment of Included Studies

The quality of the included studies was assessed using Phillips et al. (2006). The form is included in Appendix *24*. When assessing the quality of the papers, it was found that generally economic evaluations of weight-management programmes were appropriately stating the objective of the study, as well as clearly stating the perspective and decision maker. Papers were also consistent in clearly stating the options under review, clearly defining a control group and stating the baseline values and observed outcomes that were inputted into the model. The main exception to this was Ginsberg and Rosenburg (2012), which did not clearly explain the objective of the evaluation and the options being assessed were not adequately explained with a control group not being used for comparison. Ahern et al. (2017) failed to clearly define the perspective of the cost-effectiveness analysis, whilst both Gustafson et al. (2009) and Michaud et al. (2017) used a payer-perspective, but were unclear about who the payer was.

In the majority of cases, justification for the chosen model structure was rare, and alternatives to the chosen decision model were not discussed. Both Markov and simulation models were found to appropriately discuss model structure, and were transparent in their description of the process of the model. Diagrams of Markov models were common which was beneficial and improved transparency of model transitions. Cycle length was often not clearly stated, although the more recent papers have improved upon this. Mathematical models were found to be unclear about how disease progression takes place and the causal relationships within the model.

Key parameters were often discussed in detail in both Markov and simulation models, and references for parameter values were included by the majority of these. Utility values were also discussed. However, the process of identification of the parameter value papers was a common omission. Quality assessment of the data was also lacking with Thomas et al. (2017) being the only study that appropriately discussed an assessment of the quality of data included in the model.

Mathematical models were rarely transparent regarding the included utility values and values of other parameters, and it was often unclear how these values were incorporated into the decision models. Hoerger et al. (2015), Lewis et al. (2014) and Olsen et al. (2005) were also lacking in their data identification and it was not clear which parameters were included in the model. Olsen et al. (2005) was also unclear about pre-model inputs regarding the intervention that was being assessed.

Sensitivity analysis was lacking within the studies. Methodological uncertainty was the only type that was consistently assessed. Early studies rarely assessed parameter uncertainty appropriately, especially in mathematical models, but this has improved over time as the comprehensiveness of studies has progressed. Where probabilistic sensitivity analysis did not take place, the exclusion was not justified. Sensitivity analysis regarding model structure was extremely rare. Miners et al. (2012) and Roux et al. (2006) were the only two papers that assessed structural uncertainty appropriately, in which alternative functions in relation to disease states in were considered.

When considering the consistency of modelling, no discussions of thorough testing of the mathematical logic were made apparent. However, conclusions were valid across all studies, and where counterintuitive results were found, explanations were provided. There were a large number of studies however, that did not discuss their results in comparison with other economic evaluations. Neither Gustafson et al. (2009) or Michaud et al. (2017) included quality of life in their estimations of cost-effectiveness when using a payer perspective, and it was unclear whether this was appropriate. The outcomes in

Olsen et al. (2005) were found to be inconsistent with the perspective of healthcare providers and society as utility from health states was not included.

The papers that did not consider any weight-regain, Zomer et al. (2017), Bemelmans et al. (2008) and Olsen et al. (2005) were found to be low-quality studies with a lack of clear justification and transparency across the majority of the data dimensions listed in Phillips et al. (2006). Apart from this, there appeared to be little relation between weight-regain assumptions, the extensiveness of sensitivity analysis conducted regarding weight-regain, and evaluation quality. However, papers that considered long-term weight-trajectories following the regain period appeared to be generally more thorough and of higher quality than those that did not. It was found that Thomas et al. (2017), Fuller et al. (2014), Meads et al. (2014), Forster et al. (2011) and Roux et al. (2006) were of particularly good quality, with two of these being simulation models and three being Markov models, although both Fuller et al. (2014) and Forster et al. (2011) were unclear about weight-trajectories post-weight-regain.

In summary, papers have improved somewhat over time, with the more recent papers being more thorough than earlier papers, especially when considering the early mathematical papers. This may have been due to checklists such as CHEERS (Consolidated Health Economic Evaluation Reporting Standards) improving the standards of reporting in modelling studies over time (Husereau et al., 2013). However, papers must improve transparency regarding the justification of model structure and identification of parameter values and utilities. As well as this, sensitivity analysis should be more extensive in future, and consider a wider range of potential outcomes.

6.5 Discussion

This systematic review finds that there has been a growth in the number of economic evaluations of BWM interventions that employ modelling methods. Griffiths et al. (2012) specified that to capture the effects of weight-change effectively, Markov or simulation modelling should be employed. In the original review, 4 of the 7 papers (57%) assessing BWMs used either Markov or simulation models, whilst 13 of the 15 papers in the update used either of these two methods (87%). The difference in the rates that Markov and simulation models are used indicates that the modelling of cost-effectiveness when reviewing BWMs has become more sophisticated since the original Griffiths et al. (2012) review was undertaken, which should have improved the accuracy of more recent cost-effectiveness estimates. Markov modelling is the most popular form of cost-effectiveness modelling when assessing behavioural weight-management programmes, likely because of its ability to capture the effects of time, and the simplicity of the modelling when compared with patient-level simulation models.

Despite the evidence found in the previous chapter of this PhD, that many participants in weight-loss programmes regain weight in the long-run, studies continue to have deficiencies with regard to assumptions about weight-trajectories following the interventions. In some cases, studies do not consider any weight gain following the completion of the programme, which limits the accuracy of cost-effectiveness estimates. Only 4 papers reported the outcome of a programme with a duration of over 12-months. However, all models considered a time-horizon of at least 10-years, with the majority of studies considering a lifetime time-horizon. Therefore, a much larger period of model time horizons are modelled based on assumptions, rather than being based on observed outcomes. Estimation of the weight-trajectories of participants following programme completion are a key component to determining long-term cost-effectiveness

A range of weight-gain assumptions were reported in the papers. Fifteen of the 22 papers made predictions about weight-regain and further weight-trajectories after programme completion. Linear weight-regain was the most common assumption with 11 of the 15 papers taking this approach. Linear regain was either modelled in the form of a fixed amount of weight-regain per time period, for example 1kg per year, or a linear regain to either baseline weight or to match the no intervention trajectory after a certain amount of time. A problem with a fixed weight gain rate is that if this is indefinite, and the assumption is made that weight regain in the first year following the programme is equivalent to weight-gain in the 10th year following the programme, which does not follow the pattern of weight-regain described in the previous chapter. As well as this, participants are assumed to gain weight year-on-year until the end of the time-horizon, which may be unrealistic due to changes in body composition as individuals age, and a very high proportion of the cohort becoming morbidly obese (Gaddey and Holder, 2014).

Another problem with fixed average weight gain is that the assumption is made that those who lose a large amount of weight inside the programme gain weight at the same rate as those who do not lose much weight, which again, is limiting. However, if assuming a weight-loss regain to baseline weight or a no intervention trajectory within a fixed time frame, the assumption is being made that those who lose the most weight, and are therefore the most successful with weight-loss, then regain the most weight-loss following the end of the programme. This may be incorrect as, if a BWM interventions create effective, sustained weight management habits, it may be that those who lose most weight do not regain weight at a greater rate (Beeken et al., 2017).

Another assumption used in the literature was that participants regain weight at a fixed rate until they reach their baseline weight, or they match the control group weight trajectory, meaning that those who lose weight most quickly are able to maintain some weight-loss for a longer period of time. This improves upon the assumption where weight is regained to baseline within a fixed time, but also faces the limit that all individuals regain weight at the same rate regardless of their initial weight-loss, and that this weight-loss regain is linear.

Two alternatives to linear regain were also employed in modelling. The first was a decay of effect each year, where the amount of weight regained each year falls until little to no effect of the intervention remains. This is more representative of the real world, in terms of weight regain occurring quickly and slowing over time, as shown by the pattern of weight-regain found by the meta-regression analysis in the previous chapter, but only one paper from the original review, and one paper identified in the update employed this method.

The final assumption used in modelling in the papers found in this update was treating BMI categories as separate health states, where individuals transition between different BMI categories over time according to transition probabilities. This assumption captures the heterogeneity in weight-regain patterns between people, which is useful, and allows other characteristics, such as gender, age, income, BMI and weight-loss within the programme to be taken into account when inputting transition probabilities if the model works at an individual level. By using these characteristics to predict weight trajectories post-intervention, cost-effectiveness by subgroup could be estimated more accurately which would improve the ability of policymakers to target particular groups of people.

Eighteen papers reported cost-effective outcomes. A total of 7 papers also reported that a programme would also be cost-saving. This is promising for policymakers considering funding behavioural weight-management interventions as it shows that the majority of BWMs are expected to be cost-effective in the long-term.

Whilst the majority of studies did consider weight regain following programme completion, only 9 papers tested their assumption in sensitivity analysis. Briggs et al. (2012) recommends that where uncertainty is present, sensitivity analysis should be carried out when modelling cost-effectiveness. As weight-loss regain is an unknown, and the rate of regain depends on a number of influencers, testing alternative scenarios is a sensible test of the robustness of cost-effectiveness estimates (Blomain et al., 2013). Only 7 of these papers tested more conservative scenarios than the base case. Three saw large increases in their estimated cost effectiveness ratios (Gustafson et al., 2009; Roux et al., 2006; Ginsberg and Rosenberg, 2012), two were no longer cost-saving (Thomas et al., 2017; Hoerger et al., 2015), one remained cost-saving but saw a fall in the number of QALYs provided from 0.22 to 0.04 per person (Meads et al., 2014), whilst one paper found only a small impact of a 3% change in ICER for each additional 0.01BMI point gained per month (Cobiac et al., 2010).

These impacts on sensitivity analysis show the need to test weight trajectory scenarios as cost-effectiveness estimates may be sensitive to weight-regain assumptions. Whilst programmes can remain cost-effective subject to altering weight regain assumptions, policymakers can often be faced with the task of choosing between multiple potential interventions, and providing information about multiple scenarios of weight-regain will improve the decision making process.

Two studies tested more optimistic weight regain scenarios with one paper reported an increase in QALYs gained from 0.06 to 0.09, with the programme remaining cost-saving (Trueman et al., 2010). Forster et al. (2011) tested a more optimistic assumption also and saw the cost-per-DALY fall from 12,000AUD to 620AUD in one programme and 13,000AUD to 3,000AUD in another. These weight-change projections should also be validated to ensure assumptions regarding weight-trajectories reflect reality (Eddy et al., 2012).

In summary, behavioural weight-management interventions are often cost-effective, and can be cost-saving in the long-term. However, at present, the majority of cost-effectiveness models do not put enough consideration into the impact of long-term weight regain on costs and effects. Models should attempt to empirically generate values on weight regain rather than rely on assumptions alone. Where assumptions are required, a series of sensitivity analyses are required to test the impact of changing these assumptions on cost-effectiveness, due to the uncertainty in weight regain rates following behavioural weight-management interventions. The results of the model predictions, including the model traces across weight and BMI groups, should be validated to ensure realistic and intuitive results are obtained. Modelling should also consider alternatives to linear regain, such as non-linear regain or probabilities of weight-loss maintenance, in order to better capture real-world weight-regain patterns. Modelling studies should also at least employ Markov modelling and should consider patient-level simulation models to be able to incorporate individual characteristics and improve estimates of cost-effectiveness. These findings will inform the adaptation of an economic model to improve the modelling of behavioural weight-management programmes and the estimation of cost-effectiveness. The assumptions regarding long-term weight-trajectories used in the economic evaluations in this review will also be tested within the economic model, in order to identify the impact of changing assumptions on estimates of cost-effectiveness.

Chapter 7: Weight Outcomes after Behavioral Weight-Management Programs: A Meta-Analysis of Long-Term Follow-Up

7.1 Introduction

The final phase of this PhD is to modify an economic model with the aim of improving the accuracy of the cost-effectiveness modelling of weight-management interventions. The robustness of the model and uncertainty regarding long-term outcomes will be tested by adjusting various modelling assumptions, using data from the Slimming World programme as a case study. Before doing this, a number of phases must be completed to be able to predict weight-trajectories and appropriately and model cost-effectiveness. In Chapter 5, regression analyses were run using the 24-month outcome data for the Slimming World programme to predict individual weight-change, and gain an understanding of the heterogeneity in weight-change outcomes. In Chapter 6, a review of previous models found assumptions regarding weight-trajectories following behavioural weight-management programmes (BWMs) were often basic. For longer term weight-trajectories, we looked to evidence in the literature. A systematic review was undertaken with the aim of identifying BWMs that followed-up participants for at least 3 years from the start of the programme.

Behavioural lifestyle interventions have the potential to be successful in the short-term, but longer-term outcomes are less certain given that follow-up of participants after they leave the programme is rare. Slimming World has the ability to continue recording the weight trajectories of members, but only for as long as an individual continues to attend Slimming World classes. As bodyweight can have consequences for health at any time-point, weight-trajectories in the long-term are important to determining the effectiveness of a programme. Therefore, a limitation of many programmes where continued attendance is required to record results is that those who are not followed-up are unobserved. This causes uncertainty in outcomes, and these missing data can cause biased estimates of effectiveness (Kang, 2013).

Leaving a programme may not necessarily be due to the individual discontinuing their weight management. There is the possibility the individual feels they have learnt enough to manage their weight without the help of a programme, or that he/she would like to continue attending but does not have the time or money available to them. Similar assumptions are made in other behavioural change interventions. For example, in the smoking cessation intervention literature, the common assumption is that those who leave and do not respond to follow-up have resumed smoking (Blankers et al., 2016; Ussher et al., 2015). However, it is limiting to assume that all those who leave the programme or do not respond to follow-up have reverted to pre-programme habits.

The aim of this chapter is to systematically review evidence of the long-term outcomes of behavioural weight-management programmes. The following objectives are set out to achieve the aim of this chapter:

- To identify papers that report outcomes of a behavioural weight-management programme at least 3-years from the start of the programme.
- To describe these programmes in detail and extract relevant data regarding the programmes.
- To conduct meta-regression analyses to establish the influencers of weight-change.
- To use meta-regression analysis to estimate long-term-weight change.

To meet the first objective, a search strategy was designed to identify these papers, and was employed in multiple databases. Three-year outcomes were chosen as a minimum length of follow-up. This gave an extra year’s follow up when compared with the Slimming World data and, it was felt, would optimise the number of studies included. Once the papers were identified, the programmes were described to understand the approaches taken across the various BWMs, and data was extracted for use in meta-analyses. Finally, multiple meta-regressions were undertaken to establish the effects of various participant and programme characteristics on weight-change outcomes, and to predict a weighted mean long-term weight-trajectory across the included programmes. By establishing a pattern of weight-change, this chapter can help to inform a better understanding of weight-management behaviour following weight-management programmes.

7.2 Methods

7.2.1 Search Strategy

Preliminary searches were undertaken in OVID Medline to find common key terms used in papers evaluating weight loss and long-term weight outcomes. The terms found using this method were included in a full search (Table 39). Searches were run in Medline, Embase, PsychINFO and CINAHL.

Table 39: Search Terms Employed in the Search Strategy

Time-Period	Weight	Intervention Type
Long-term	Weight-loss	Lifestyle
Follow-up	Weight-maintenance	Behavio*
Longitudinal	Diet ADJ3 maintenance	
3-year*	Weight-traject*	
Three-year*	Weight-gain	
4-year*	Weight ADJ3 change	
Four-year*		
5-year*		
Five-year*		

The aim of the search was to identify papers that reported the long-term weight outcomes of behavioural weight management programmes. For the search, the terms in each of the columns in Table 39 were combined using the ‘OR’ operator, and each column was combined using the ‘AND’ operator. Therefore, for papers to be identified, they were required to include at least one term from each column. For the Medline, Embase and PsychINFO search, titles were searched for all terms, except for ‘weight-traject*’ which was searched as a key term as few papers included the term in the title, and the terms ‘lifestyle’ and ‘behavio*’ were required to be in the abstract. In the CINAHL search, ‘weight-traject*’ was also required to be included in the title for convenience. This approach was formed in an iterative process, and the strategy provided a manageable amount of papers which included key papers for meeting the aims of the review.

To add further focus to the search, the terms ‘cognitive’, ‘surgery’, ‘disorder’, ‘medicat*’, ‘mother*’, ‘depression’, ‘pregnan*’, ‘gastric’, ‘bariatric’ were included in the search as keywords using the operator ‘NOT’ to avoid papers that focussed on surgical interventions, pharmaceutical interventions, pregnancy and individuals with metal health issues. These operators were included to reduce the number of inappropriate papers that the search identified in relation to the inclusion criteria listed below.

Papers were limited using filters in OVID and CINAHL to be in the English language, to involve only adults, and to have been published within the last 15 years to ensure all behavioural weight-management programmes identified were relevant to today’s environment. Citation tracking was then performed on the included papers.

7.2.2 Inclusion/Exclusion Criteria

In order to ensure that only relevant papers were included in the systematic review, inclusion and exclusion criteria were set. The inclusion criteria were as follows:

- The participants in the study were adults (16+)
- The paper evaluated a lifestyle/behavioural weight-management programme
- The primary aim of the programme was weight-management
- The paper reported weight-change between at least two-time points with the final time-point being a minimum of 3-years after baseline

Papers were excluded if:

- The programme focussed on a population with a particular condition not relating to weight (programmes targeted at a population of individuals with type 2 diabetes were not excluded as type 2 diabetes is strongly related to obesity)

- The programme offered pharmacotherapy or surgery as a treatment option, either alone or alongside the behavioural programme

- The programme's primary focus was an alternative outcome to weight-management (such as improved mental health or reduced knee pain)

All papers identified were screened based on title and abstract. Following screening, all papers that were remaining were then read in full and then checked against the criteria once again. All the remaining papers were included in the review. A second reviewer screened the titles and abstracts of 20% papers identified. The included papers were agreed upon after discussion.

7.2.3 Data Extraction

Data were extracted using a bespoke data extraction form. Columns with the following headings were used to collect data from each of the nine included papers in the extraction form:

- Country
- Programme
- Population
- Follow-up Length
- Initial n
- Follow-up n
- Initial weight-change
- Follow-up weight-change
- Measurement method
- Limitations
- Comments

These headings were chosen in order to understand the components of the programmes and the populations involved in the programmes. In addition, specific baseline and outcome data were recorded to be used in meta-analyses.

For the purpose of the meta-regressions, outcomes reported as percentage change or BMI change were converted into kilograms. The conversion from

BMI to kilograms used either a reported mean height in the study when possible, and if not, a height of 5’4”, to represent the average height of a woman, was used (for studies that only included females). Observations for women and men were recorded separately where possible. Where standard errors were not reported, standard deviations and confidence intervals were converted to standard errors using the formula in Equation 33, where standard error (SE) equals the standard deviation (SD) divided by the square root of the sample size (n).

Equation 33

$$SE = \frac{SD}{\sqrt{n}}$$

Where weight-loss figures were reported by group, for example weight-loss by BMI category, a mean value for weight-loss was calculated, and a pooled standard deviation was calculated using the formula in Equation 34, before converting this pooled standard deviation to standard error.

Equation 34

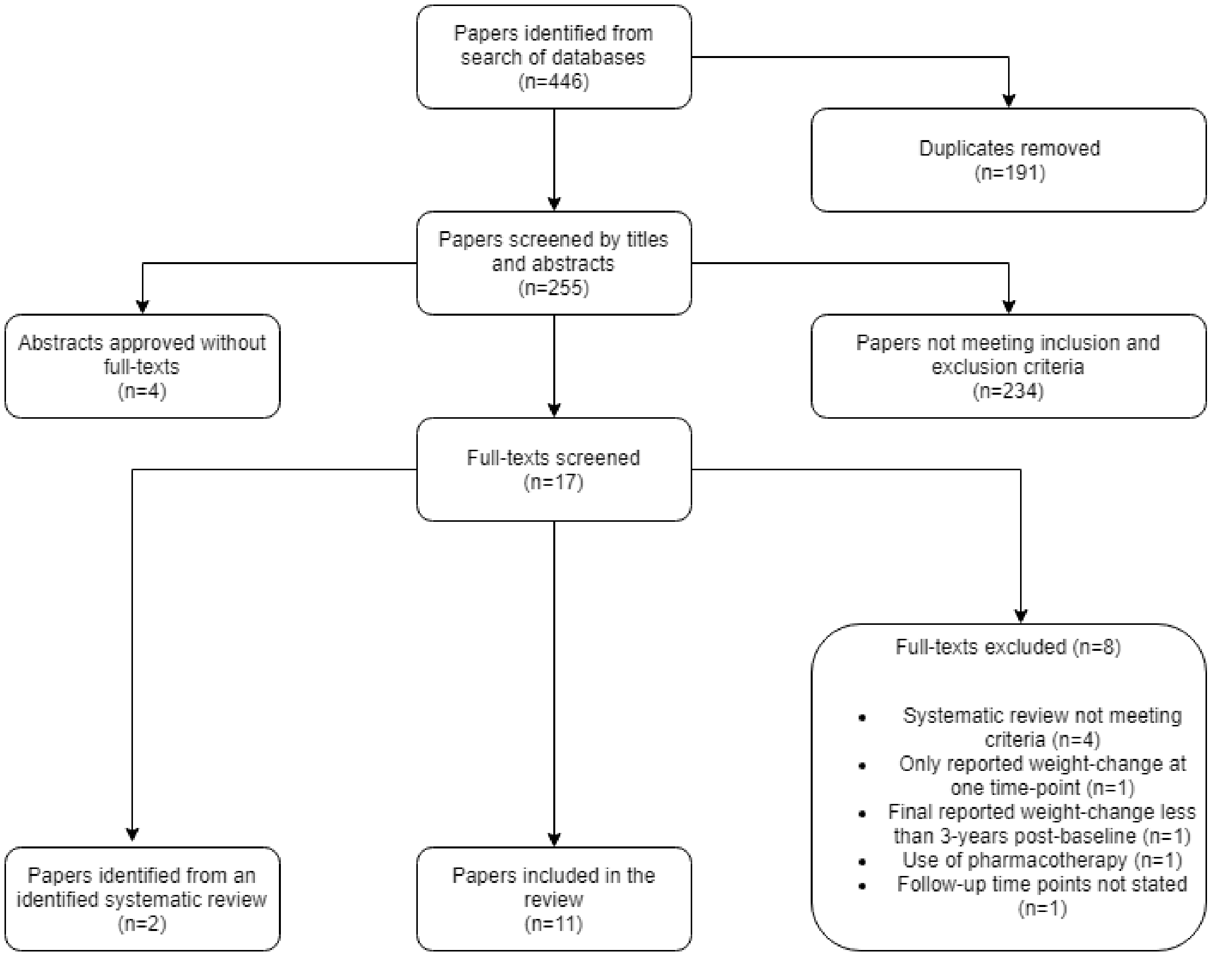
$$SD_{pooled} = \sqrt{\frac{SD_1^2 + SD_2^2 + \ldots + SD_n^2}{n}}$$

7.3 Results

7.3.1 Search Results

The search was run in February 2018 and updated in January 2019. The final search identified 255 unique papers. After screening the titles and abstracts, 17 papers were selected to be read in full, of which eight were excluded in line with the stated criteria. In addition, a further two papers were identified from a systematic review which fit the inclusion criteria, resulting in a total of eleven full-texts for inclusion in the review. Citation tracking was performed on the included papers, but this yielded no additional studies. The flowchart of the search strategy is shown in Figure 20, below.

Figure 20: A Flowchart of the Search Strategy



7.3.2 The Behavioural Weight-Management Programmes

Thirteen behavioural weight-management programmes were identified across the 11 papers included in the studies, as some papers contained multiple BWMs. A summary of the programmes is presented below:

A diabetes-prevention intervention based in Poland, DE-PLAN, was the focus of Gillis-Januszewska et al. (2017). The programme was based on behaviour-change with five lifestyle goals: weight-loss, reduced fat intake, increased consumption of fruit and vegetables, and increased physical activity. Participants were those aged 25 or older with a high diabetes risk. Nurses with specialised training delivered a 10-month intervention with a 4-month intensive phase where participants were given one individual session followed by 10 group sessions. Participants were given verbal advice by nurses on diet and physical activity changes as well as printed materials. Participants were also invited to participate in organised physical activity twice a week. The maintenance phase which followed the intensive phase consisted of motivational phone calls and letters. Participants were weighed on-site at baseline, 12-months and 36-months. Two hundred and sixty-two patients were invited to participate after screening; of these 105 completed all 3 measurements.

Seguin et al. (2017) evaluated the long-term effects of the Strong Women–Healthy Hearts Programme, an evidence-based programme which operated in 22 states across the United States. The programme comprised of two hour-long weekly classes over a 12-week period. Participants were given advice about dietary behaviour change and regular aerobic exercise in a community setting. Of the participants in the original study, 600 were invited to participate in a follow-up survey either online or on paper. Of the 600 invited, 165 responded, with 154 having complete data for baseline weight, post-programme weight and follow-up weight. Follow-up weight were recorded at 3-years from the start of the programme. The sample consisted of woman aged 40 or above who lived alone, were sedentary, and had a BMI of 24kg/m^2 or higher at baseline.

The long-term effectiveness of a weight-loss intervention, which was part of the Prevention of knee Osteoarthritis in Overweight Females (PROOF) study, a Dutch randomised controlled trial for women aged between 50 and 60, was evaluated by De Vos et al. (2016). Participants in the intervention group met with a dietitian and discussed their current diet and activity, with goals mutually agreed by the dietician and participant. The first three appointments occurred fortnightly with the remaining sessions planned through mutual agreement with the total meeting time per year being 4 hours. Physiotherapists also led 20 weekly classes which were low-intensity and aimed at finding sporting activities that participants "could enjoy and maintain until after the intervention" (De Vos et al., 2016). The intervention lasted for a total of 2.5 years. At 6.6 years, participants were visited at home by a research assistant and weighed. Of the 407 participants that were randomly assigned, 366 completed the 2.5-year programme and 247 agreed to follow-up at 6.6-years. De Vos et al. (2016) reported outcomes for the intervention group relative to the control group, who were offered no intervention. As the control group weight-change was close to zero at the end of the intervention and at the final follow-up, the outcomes reported in De Vos et al. (2016) were still included in the meta-analyses.

Rolland et al. (2014) performed a retrospective analysis on participants of LighterLife Total, a UK-based commercial weight-management programme, who had weights available at baseline and at least 12-months. The programme was designed for individuals with BMIs of 30kg/m^2 and higher. The programme comprised of a three-pronged approached using a VLCD, group support and behavioural therapy. The aim of the study was to help participants achieve weight-loss and to enable participants to improve their weight-management ability. Following the initial weight-loss phase, which lasted for a mean of 20 weeks, participants attend weekly group meetings to encourage improved weight-management behaviour. Participants were allowed to re-enter the weight-loss phase when it suited them. Weight measurements were recorded weekly in group sessions with 580 of the initial 5965 participants having a weight recorded 3-years after the end of their initial weight-loss phase.

Two programmes from the Look Action for Health in Diabetes (AHEAD) study were included in the meta-analyses, with outcomes at different time-points being reported by the Look AHEAD Research Group (2014) and Wadden et al. (2011). The participants, who were from United States, were between 45 and 76 years of age, were overweight and had type 2 diabetes, were randomised into either an intensive lifestyle intervention of a diabetes support and education group. The six months of the intensive lifestyle intervention was delivered in the form of three group meetings and one one-to-one meeting per month with a healthcare professional (dieticians, psychologists and exercise specialists). For the next 6 months, participants attended two group sessions and one one-to-one meeting per month. Participants were prescribed dietary guidelines, meal plans and meal replacements for the first 4-months with the guidelines being less strict from months 5-12. Physical activity was prescribed with those achieving the recommended amount being prescribed more. Participants were encouraged to record food intake and physical activity.

From years 2-8, Look AHEAD targeted weight-loss maintenance and helping those who did not lose weight initially with their weight-loss goals. In years 2-4, participants had an individual meeting and a telephone or email discussion each month. In years 5-8 the participants were only provided with the individual monthly on site meeting. Participants were also offered monthly group meetings in years 2-8. The group sessions consisted of being weighed and discussing diet, physical activity and lifestyle change. The dietary support and education group consisted of three meetings per year, for the first 4 years, in which participants discussed diet, physical activity and social support. The healthcare professionals that ran the sessions provided information regarding diet and physical activity but did not prescribe specific behavioural strategies to help participants adhere to the recommendations. In years 5-8, participants met once yearly. Any participants in the group who was interested in greater support was referred to their primary care doctor. A total of 5,145 individuals were randomised into the study with 4,585 of these providing outcomes 8 years after randomisation.

Kuller et al. (2012) evaluated the Women on the Move through Activity and Nutrition (WOMAN) study in which participants from the United States were randomised to either a lifestyle change or health education group. Both of these programmes focused on behavioural change and so were included in the meta-analyses. Eligible participants were between the ages of 52 and 62 with a BMI of between 25kg/m^2 and 39.9kg/m^2 amongst other criteria. The health education group were provided with six educational seminars in the first year of the intervention and several times per year over the next 36 months. The lifestyle change intervention was a group-based programme delivered by a team comprised of nutritionists, exercise physiologists, and psychologists. The first year of the programme consisted of 40 visits to the clinic with monthly visits thereafter. Because of a lack of funding, the lifestyle change programme ended approximately 36-months after baseline with therefore “little to no intervention” being provided between 36-months and 48-months (Kuller et al., 2012). Physical activity was introduced after 6-months with participants being set targets to achieve in their own time. Of the 508 participants that were randomised, 456 completed the 48-month evaluation.

The Treatment of Underserved Rural Settings (TOURS) study was evaluated by Millsom et al. (2011). The study took place in the United States over the course of six months in which participants attended 24 weekly group sessions, delivered by a professional in family and consumer sciences, nutrition, psychology, exercise science, or another related field. The study focused on improving behavioural skills of participants such as goal setting and reinforcement. Dietary and physical activity goals were set by participants with the aim of weight-loss and were encouraged to log their caloric intake and physical activity. After the completion of the six-month programme, participants were randomised to one of face-to-face counselling, telephone counselling, or mail-only contact as an extended care programme for the next year. Face-to-face counselling consisted of two monthly group meetings, telephone counselling involved 2 monthly phone calls whilst those in the mail-only contact group were sent two weight-management newsletters each month. Participants were then followed up 2.5 years later – 4 years after baseline. A total of 234 participants were recruited for the TOURS study with 220 completing the 18-month extended-care phase and 110 responding the final follow-up.

Christiansen et al. (2007) evaluated a retrospective follow-up for participants of a Danish private health resort for weight-loss. The programme consisted of an intensive lifestyle modification programme which participants attended for a mean of 21 weeks, with participants living onsite. Participants were treated by a group of supervisors including dieticians, physical therapists and a psychologist. Participants were provided a low-calorie diet, group-based physical activity sessions, health education and behavioural techniques. Participants who attended for a minimum of 8 weeks of treatment were contacted at 3 and 4 years. Three cohorts of individuals with severe obesity were followed-up – a 2-year follow-up, a 3-year follow-up and a 4-year follow-up. Only the 3-year and 4-year cohorts were included in this review, which consisted of 196 and 161 individuals respectively. Of the 196 and 161 individuals, 123 and 99 met all inclusion criteria and had complete data available. Follow-up data was recorded using a postal survey followed by a telephone interview.

Van Strien et al. (2007) analysed the effect of a weight-management intervention on a prospective cohort of Dutch individuals with newly diagnosed type 2 diabetes across 33 general practices. All participants received a referral to a dietician after diagnosis and were provided with individually tailored advice regarding dieting. Participants attended a total of 2 appointments with the dietician. Participants were weighed within the practice 8-weeks from their diagnosis date, and then again 4-years from diagnoses. Eighteen of the 97 participants were not weighed at 8-weeks but all 97 individuals were weighed at 4-years.

Lantz et al. (2003) reviewed the outcomes of a Swedish trial where participants were randomised to a 2-year programme either with or without an initial VLCD. Those in the VLCD group were provided with a meal replacement milkshake during the VLCD phase and then reintroduced to a conventional low-calorie diet after 12-weeks. Participants in the non-VLCD group began the programme with a conventional low-calorie diet. Participants met a dietician every 6 months for individual guidance. Programme attendees also met with a nurse or dietician in in weeks 1, 2, 4, 6, 8 and then every 4 weeks thereafter for support and additional information about nutrition, behavioural strategies for weight-management, and improving physical activity. Individuals randomised to the VLCD group began this phase after 12-weeks. Participants were also offered group cooking classes as well as groups for swimming and physical training.

After the initial 24-month weight-loss phase in Lantz et al. (2003), participants were offered a support programme for a further 2-years. Participants were weighed at 24-months, 48-months and 96-months. Eighty-seven of the initial 113 individuals who began the programme completed measurements at 24-months. Fifty-five of these completed measurements at 48-months. A total of 96 individuals were measured at the final follow-up (a mean of 87.5 months).

Table 40 shows a summary of the 13 BWMs. All programmes offered lifestyle guidance and behavioural support. Eight of the 13 programmes offered physical activity sessions, whilst 3 used a VLCD as the basis for weight-loss.

Nine of the 13 programmes offered an extended maintenance period whilst 10 of the 13 programmes followed-up individuals after they left the programme. The programmes that did not follow-up participants after they left the programme reported weight-change at the end of the maintenance phase.

Table 40: A Summary of the Included BWMs

Intervention	Weight Loss Phase Length (months)	Programme Length (months)	Last Follow-up from Weight-Loss Phase End (months)	Activity Programme	VLCD Included	Maintenance Phase Included	Participants Followed-up After Leaving
Gillis-Januszewska et al. (2017)	12	12	24	Yes	No	No	Yes
Seguin et al. (2017)	3	3	33	Yes	No	No	Yes
De Vos et al. (2016)	6	30	74	Yes	No	Yes	Yes
Rolland et al. (2014)	4.6*	40.6	36	No	Yes	Yes	No
Look AHEAD (2014)/ Wadden et al. (2011, Lifestyle Intervention)	12	96	84	Yes	No	Yes	No
Look AHEAD (2014)/ Wadden et al. (2011, Support and Education)	12	96	84	No	No	Yes	No
Kuller et al. (2012, Lifestyle Group)	6	30	42	Yes	No	Yes	Yes
Kuller et al. (2012, Education Group)	6	30	42	No	No	Yes	Yes
Milsom et al. (2011)	6	18	42	No	No	Yes	Yes
Christiansen et al. (2007)**	4.83	4.83	37.17	Yes	No	No	Yes
Van Strien et al. (2007)	1.84	1.84	46.16	No	No	No	Yes
Lantz et al. (2003, VLCD)	24	48	72	No	Yes	Yes	Yes
Lantz et al. (2003, Non-VLCD)	24	48	72	No	No	Yes	Yes

*Rolland et al. (2014) did not have a fixed weight-loss phase and reported the mean initial weight-loss phase length
**The figure for follow-up time are taken from a mean of the 36 and 48-month follow-ups from the two cohorts in Christiansen et al. (2007)

Across the 13 programmes, there were a wide range of methods employed by programme providers for weight-management, the duration of the weight-loss phases, weight-loss maintenance support, and the time from baseline to the final follow-up. Table 41, below, shows a summary of the length of the weight-loss phases, the full programme length including any maintenance phase, and the length of time between the end of the weight-loss phase to the final follow-up. The mean weight-loss phase lasted for just over nine months whilst the mean final follow-up weight-change recorded in each programme was just under 4 and a half years from the completion of the weight-loss phase.

Table 41: A Summary of the Time Periods in the Programmes (months)

Variable	Mean	Min	Max
Weight-Loss Phase (months)	9.41	1.84	24
Programme Length (months)	35.25	1.84	96
Final Follow-up from Weight-Loss Phase End (months)	52.95	24	84

7.3.3 Study Population

Across the 13 programmes, a total of 12,769 participants were included and measured at the end of the weight-loss phase. At the final follow-up, outcomes for 6,254 were available, which represented 49% of the population who were measured at the end of the weight-loss phase. The majority of participants were women (78.6%) with 5 of the 13 programmes consisting of women exclusively. The mean baseline bodyweight across the programmes was 99.1kg with the range of mean starting body weight across the programmes being 81.5kg to 142kg. The mean age across studies was 52.1 years old, with the youngest sample being 39.6 and the oldest being 60.8 years of age.

7.3.4 Weight-Change Outcomes

After reviewing the approaches and populations in each of the weight-management programmes, the weight-change outcomes of each programme were assessed. The summary of weight change in Table 42 shows a large range of weight change at programme completion and weight change after the programme end.

Table 42: Weight-Change in Each Programme

Intervention	Weight Change at Weight Loss Phase Completion (kg)	Weight Change from Baseline to Programme Completion (kg)	Weight Change from Baseline to Final Follow-up (kg)	Weight Change from Weight Loss Phase Completion to Follow-up (kg)
Gillis-Januszweska et al. (2017)	-2.27	-2.27	-1.14	1.13
Seguin et al. (2017)	-1.32	-1.32	-5.02	-3.70
De Vos et al. (2016)	-2.18	-1.78	-0.95	1.23
Rolland et al. (2014)	-25.70	-12.90	-12.90	12.80
Look AHEAD (2014)/ Wadden et al. (2011, Lifestyle Intervention)	-8.57	-4.28	-4.28	4.29
Look AHEAD (2014)/ Wadden et al. (2011, Support and Education)	-0.59	-2.05	-2.05	-1.46
Kuller et al. (2012, Lifestyle Group)	-7.80	-5.70	-3.40	4.40
Kuller et al. (2012, Education	-1.20	-0.40	-0.20	1.00
Milsom et al. (2011)	-9.88	1.73	4.10	13.98
Christiansen et al. (2007)	-21.71	-21.71	-8.15	13.56
Van Strien et al. (2007)	-2.94	-2.94	0.04	2.98
Lantz et al. (2003, VLCD)	-9.20	-9.20	-0.46	8.74
Lantz et al. (2003, Non-VLCD)	-6.30	-6.30	-0.46	5.84

The study with the largest weight loss at the final follow-up was Rolland (2014), with participants maintaining 12.9kg of this weight-loss. The participants in

Milsom (2011) had the least successful weight-change with the mean weight gain being 4.1kg between baseline and the final follow-up.

Only two programmes saw continued weight loss following the weight-loss phase – Seguin et al. (2017) and the Look AHEAD (2014) support and education group. Overall, from the 13 programmes listed in Table 42, all 13 reported weight-loss at the end of the weight-loss phase. The individuals in 11 of the 13 programmes maintained at least some weight-loss on average compared with baseline. This pattern is illustrated in Figure 21, which shows the mean weight trajectory for the participants of each of the 13 programmes. Generally, participants reach their maximum weight-loss at the first observation, with weight then gradually being regained over time.

Figure 21: Mean Weight Trajectories from Baseline for Each Programme

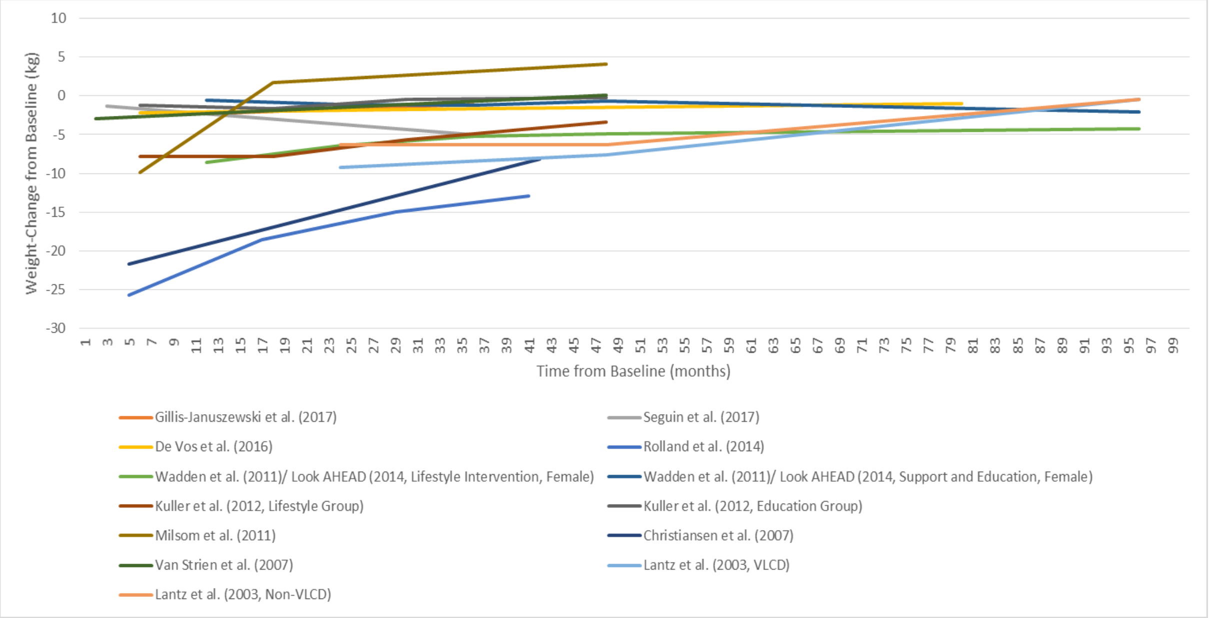


Table 43 shows a summary of weight change in each time period for each of the programmes. The greatest mean weight-loss is at the end of the weight-loss phase with participants losing 7.7kg on average. The participants on average then regain 5kg of this weight-loss between the end of the weight-loss phase and the final follow-up, leaving them with a bodyweight 2.7kg lower than baseline. The greatest standard deviation is at the end of the weight-loss phase with the smallest being on the weight-change between baseline and the final follow-up.

Table 43: A Summary of Weight Change in the Programmes

Weight Change Period	Mean	Min	Max
Weight Change at Weight Loss Phase Completion (kg)	-7.67 (7.89)	-25.70	-0.59
Weight Change at Programme Completion (kg)	-5.32 (6.27)	-21.71	1.73
Weight Change from Baseline to Final Follow-up (kg)	-2.68 (4.26)	-12.90	4.10
Weight Change between the Weight-Loss Phase and the Final Follow-up (kg)	4.98 (5.75)	-3.70	13.98

Standard deviations in parentheses

The greatest standard deviation on the mean results across the 13 programmes was around the weight-change at the end of the weight-loss phase, which could be because those in the programmes that lose the most weight in the short-term regain more weight which leads to a smaller range of weight-change at later observations.

The results here have illustrated the substantial heterogeneity between the outcomes of the BWMs, with a large range of weight-change being shown between the 13 programmes at the end of the weight-loss phase, and following the weight-loss phase. This heterogeneity was explored in meta-regression analysis in the next section.

7.4 Meta-Regression Analysis

The purpose of meta-analysis is to combine data from a number of studies to estimate an overall effect size. Meta-regression analysis was chosen as the most appropriate method of combining the studies in this review to make predictions about weight trajectories. The first reason for this choice is that individual patient level data was not available and meta-regression analysis is able to analyse data at a study level. The second reason is that meta-regression analysis is able to give a weighting to different studies based on sample size and the variance in results, which effect the estimate of overall effect. Meta-regressions can also be used establish relationships between weight change outcomes and both programme and participant characteristics. These relationships can then be used to make predictions of weight-trajectories based on the impact of programme and participant characteristics. Guidance for the meta-regression analysis was taken from Harbord and Higgins (2008).

Amongst the 11 programmes included in this review, there exists substantial heterogeneity. To explain this heterogeneity, meta-regressions were performed to identify the key predictors of weight change in the programmes and therefore, identify the cause of the heterogeneity in weight outcomes. The analysis was run in STATA 13.1 (StataCorp, 2013).

7.4.1 Meta-Regression Analyses Methodology

The first stage of the meta-regression analyses was to investigate the heterogeneity in weight-loss outcomes. The initial meta-regression predicted weight-change in the initial weight-loss phase from each programme using various programme and participant characteristics as explanatory variables. The meta-regression equation is shown in Equation 35 where W is weight, A represents mean age at baseline, G represents the percentage of females in the study, W_0 is start weight, and pl is the length of the weight loss phase of the intervention. Two binary variables, pa and V, were included for whether the programme included a physical activity programme or a VLCD respectively. These variables were chosen as they were identified as potential influencers of weight-change that were reported in each of the 13 programmes. The age, gender and start-weight of the individuals were all assumed to have an influence on each individual's desire and ability to lose weight, whilst the characteristics of the programme were assumed to affect how much weight participants lost.

Separate observations were used for females and males in the programmes from Wadden et al. (2011)/Look AHEAD (2014), Van Strien et al. (2007) and Lantz et al. (2003). Also, as Christian et al. (2007) reported the outcomes for the 3-year cohort and 4-year cohort separately, and so the two cohorts were used as separate observations too. Therefore, there were a total of 19 observations recorded across the 13 programmes at the end of the weight-loss phase.

Equation 35

$$\Delta W = \beta_0 + \beta_1 A + \beta_2 G + \beta_3 W_0 + \beta_4 pl + \beta_5 pa + \beta_6 V + \varepsilon$$

Before running multi-variate regressions, univariate regressions were run with weight loss in the weight-loss phase as the dependent variable, using the explanatory variables in Equation 35 as the predictors of weight-loss. These univariate regressions were run to identify the relationship between each included variable and weight-loss. Baseline weight was used as a control variable as weight-loss independent of start weight was of more interest as those who weigh more may lose weight more easily due to higher metabolic rates that come with a greater body mass.

Multivariate meta-regression analysis was then performed, with the aim of gaining information regarding the factors that influence weight-loss within the weight-loss phases and how much weight individuals are predicted to lose within weight-loss phases. The outcomes were presented as weighted mean values of weight change in kilograms, as were parameter estimates.

The second stage of the meta-regression analyses included all observations of weight-change from baseline that were recorded after the end of the weight-loss phase. In total, 41 observations were recorded across the 13 programmes. For the second stage, additional variables were added to the meta-regression equation from the first stage, shown in Equation 36. The first variable added was the initial weight-loss in the weight-loss phase, ΔW_0. The second was the intervention length, il, which states the full length of time participants were engaged with the programme, including any extended maintenance phases. A binary variable, M, was included to denote whether the observation was taken during a maintenance phase. Again, all three variables were assumed to influence weight-change as they affect either individual ability or the characteristics of the programme. As all observations were taken during either a maintenance phase or at follow-up, no term for follow-up was included. The final variable in the equation indicates the number of months after the weight-loss the observation was recorded at. Again, univariate regressions were run before the multi-variate analysis, with start weight, the time from the end of the weight-loss phase, and the weight-loss within the programme being used as control variables. The time from the end of the weight-loss phase was included as there was a large range in the time of follow-up, and impact of time to follow-up was not the interest of univariate regressions. Weight-loss within the programme was used as a control variable to focus the univariate regression results on the impact of explanatory variables on weight-change following the programme independent of how much weight was lost in the programme. A Monte Carlo permutation test was also used to predict adjusted p-values with 10,000 permutations.

Equation 36

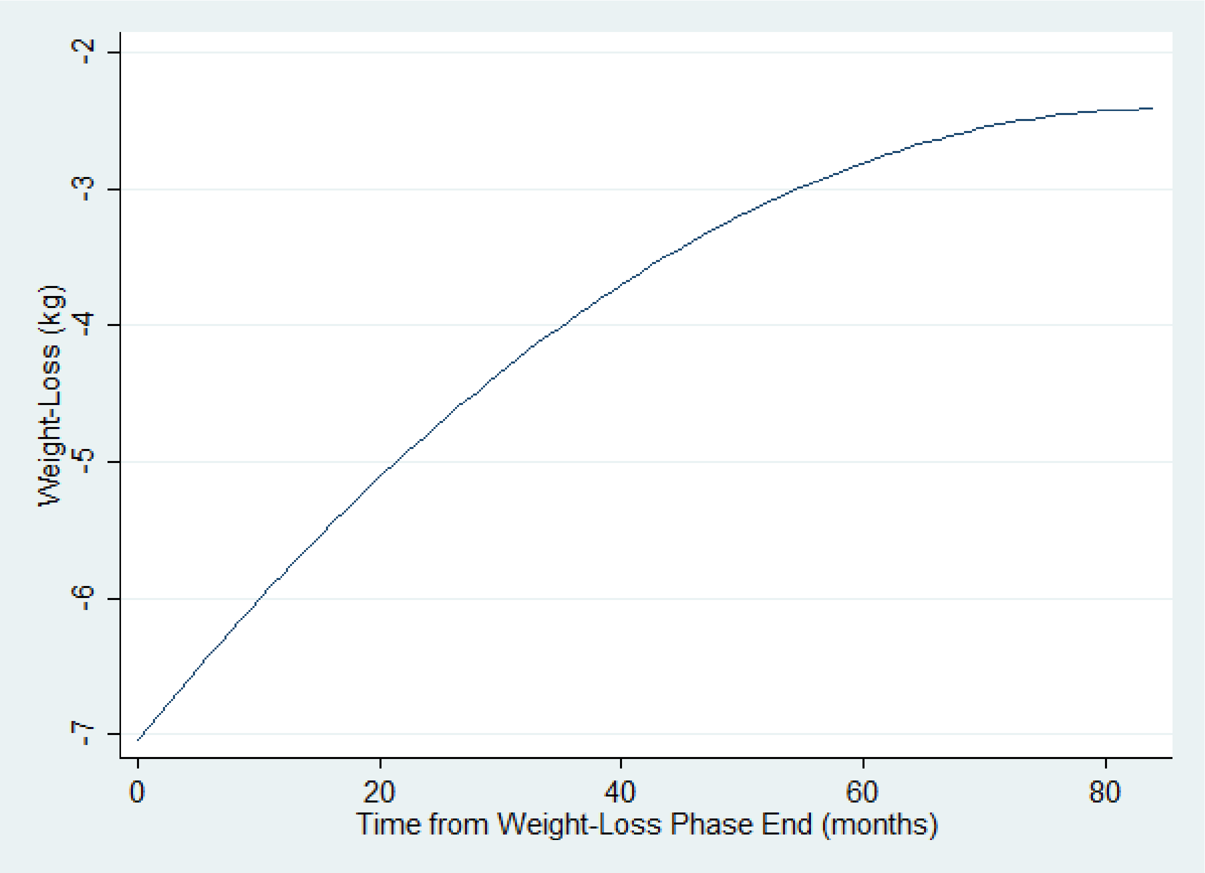
$$\Delta W = \beta_0 + \beta_1 A + \beta_2 G + \beta_3 W_0 + \beta_4 pl + \beta_5 pa + \beta_6 V + \beta_7 \Delta W_0 + \beta_8 il + \beta_9 M + \beta_{10} T + \varepsilon$$

The assumption of linearity was reviewed for the relationship between the time in the weight-loss phase and weight-loss. In the Slimming World data, the majority of weight-loss occurred initially, with weight-loss slowing down each month. This is intuitive as individuals tend to lose the most weight early on in interventions due to a greater motivation to lose weight, as they are furthest from their ideal weight (Ruhm, 2012). However, this motivation is reduced over time as self-control is depleted and weight-loss slows down, as discussed in the habits and self-control theoretical framework in Chapter 3 (Dragone, 2009; Djawadi, 2014). In order to capture this non-linear relationship, the models included quadratic terms (Alexopoulous, 2010). Without using a quadratic term, the coefficient would have to be interpreted as if each additional month provided an identical effect on weight-change, which is inaccurate.

The assumption of linearity was also reviewed for the relationship between time from the end of the weight-loss phase and weight-loss. This was due to the hypothesis that most regain occurs in the first month after leaving the programme, with each additional month having a decreasing rate of regain. This pattern was also shown to be prevalent in the literature (Ross et al., 2018). One reason for this pattern is that when individuals diet, their metabolisms slow down, and therefore, if individuals return to their pre-intervention habits, they will gain weight quickly, with the weight-gain slowing over time as the metabolism returns to normal (Blomain et al., 2013).

When plotting the relationship between the two variables, the assumption of linearity for regression did not hold. This was because the relationship between the time variables and weight-change was non-linear, as shown in Figure 22 below, with the effect decreasing with time.

Figure 22: A Graph of Weight-Change from Baseline against Time from the End of the Weight-Loss Phase



Using a quadratic term was judged to be the best option as the meta-regression model could remain linear, which would be beneficial as other relationships in the multivariate model had linear relationships with the dependant. As well as this, a linear model enabled easily interpreted results for estimating the relationships between the independent variables and the dependent when compared with the use of non-parametric regression models (Whitley and Ball, 2002). As well as this, the dependant variable could remain as a continuous variable and predictions of weight-loss could be made using the model, which wouldn't be possible with a logistic regression (Sperandei, 2014).

A quadratic term was used rather than a cubic term as there was only one curve in each relationship, and introducing cubic terms hampered the fit of the model, as quadratic terms were found to provide the best fit.

After identifying the influencers of weight-loss and weight-loss maintenance, the aim of the final meta-regression was to establish a pattern of weight-loss trajectory following the end of the weight-loss phase. This meta-regression used all observations recorded – both at the end of the weight-loss phase and at follow-up time points. The aim of this stage was use the observations of weight change alongside the predictors of weight change in order to predict weight-change at each time point across all individuals. After running the meta-regression, weight-change was predicted and plotted against the time from the end of the weight-loss phase to illustrate the pattern of weight-regain following the end of a weight-loss programme.

7.4.2 Meta-Regression Analyses Results

The univariate meta-regressions predicting weight-loss in the weight-loss phase, shown in Table 44, were performed using baseline weight as a control variable. The regressions found that age and the weight-loss phase being longer predicted less weight-loss. As the length of the weight-loss phase had a non-linear relationship with weight-loss, a squared term for weight-loss phase length was also included with the weight-loss phase variable, and vice-versa. This variable predicted that the impact of each additional month of the weight-loss programme reduced weight-loss by 0.005kg. Being female, having a greater starting weight, the programme including physical activity sessions, and the programme using a VLCD predicted more weight-loss within the weight-loss phase. Age and start weight had significant effects on weight-loss at the 5% level.

Table 44: Univariate Meta-Regressions on Weight-Loss in the Weight-Loss Phase

Variable	Coefficient	t-statistic
Age (years)	0.748*	2.46
Female (%)	-4.809	-1.32
Start Weight (kg)	-0.253**	-3.33
Weight-Loss Phase Length (months)	0.549	0.68
Weight-Loss Phase Length Squared (months)	-0.00586	-0.20
Physical Activity Programme	-2.154	-0.70
VLCD	-7.412	-1.91

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

Two multivariate meta-regression models were run, with the results shown in Table 45. The first model used Equation 35, as well as the squared term for weight-loss phase length, and predicted a weighted mean weight-change of -7.92kg (7.07kg standard deviation) was predicted. The multivariate meta-regression found that only the programme including a VLCD programme predicted more weight-loss at the 5% level (p=0.03). Overall, the variables explained 70.72% of the between study variance. The joint test for all covariates gave a p-value of 0.0027, which implies there is evidence to suggest the covariates are significant predictors of weight-change. The model also produced an I^2 statistic of 99.15%, which implies significant heterogeneity, and that meta-regression was an appropriate method of analysis.

The second model did not include programmes that used a VLCD programme, due to the question of whether VLCD programmes are comparable with non-VLCD programmes. This meant 3 observations were removed from analysis – Rolland et al. (2014), and the two VLCD observations from Lantz et al. (2003). Without VLCD programmes included, 69.62% of variance was explained by the model, which predicted a weight-loss of 6.52kg (6.08 standard deviation), with no variables being significant at the 5% level. The joint test of covariates here produced a p-value of 0.0073, which again suggests the covariates are significant predictors of weight-change, even without the VLCD programmes included. The I^2 statistic again revealed a large amount of variance attributable to residual heterogeneity with a value of 99.29%.

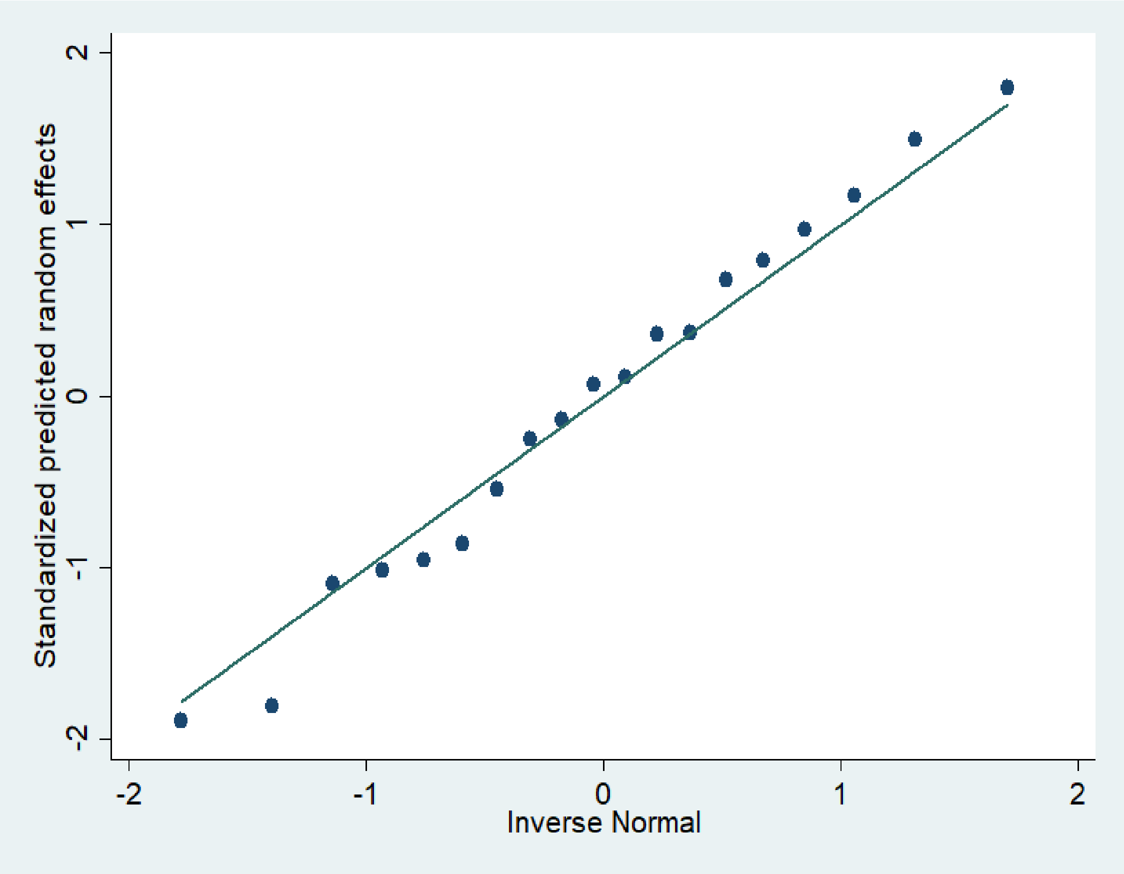
Table 45: Multivariate Meta-Regression Models Predicting Weight-Loss in the Weight-Loss Phase

Variable	Coefficient (full model)	t-statistic (full model)	Coefficient (no-vcld)	t-statistic (no-vlcd)
Age	0.501	1.44	0.225	0.66
Female	-0.457	-0.15	-2.279	-0.79
Start Weight	-0.154	-1.20	-0.223	-1.85
Weight-Loss Phase Length	-0.311	-0.47	0.0444	0.07
Weight-Loss Phase Length Squared	0.0303	1.22	0.00885	0.36
Physical Activity Programme	-1.130	-0.46	-2.208	-0.99
VLCD	-9.485*	-2.53	-	-
Constant	-18.48	-0.60	4.766	0.16
N	19		16	

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

After finding both models were predictive in multivariate analysis, model checking was performed for the full model as it was a better predictive model. The first step was to use a Q-Q plot to check whether any outliers were present in the data, and to check the assumption of normal random effects. Figure 23 shows a close to normal distribution which implies the assumption of normal random effects was met.

Figure 23: Normal Probability Plot of Standardised Predicted Random Effects for the Weight-Loss Phase



Following the analysis of the weight-loss phases, long-term follow-up outcomes were analysed. The second stage of the meta-regression analyses began by performing univariate regression analysis using the variables in Equation 36. Again weight-loss phase length was included as a squared term, as was the length of the full programme including any maintenance phases, and time from weight-loss phase end due to the non-linear relationship with weight-loss.

The results of the univariate meta-regressions are shown in Table 46 with each of the variables being a predictor of weight-change at observations recorded after the end of the weight-loss phase. As mentioned before, start weight, weight-lost in the weight-loss phase, and time from the end of the weight-loss phase were included as control variables, as was weight-loss squared due to the non-linear relationship between with weight-loss. Three variables were significant at the 5% level – initial weight change, with each additional kilogram of weight-loss predicting 0.52kg more weight-loss in the long-term, the full programme length, and whether the programme had a maintenance phase. These two also both predicted more weight-change, which is intuitive as programme with maintenance phases are generally longer programmes.

Table 46: Univariate Meta-Regressions on Weight-Change in Follow-up Observations

Variable	Coefficient	t-statistic
Age	0.165	1.33
Female	1.00528	0.71
Start Weight	0.0178	0.48
Weight-Loss Phase Length	-0.421	-1.34
Weight-Loss Phase Length Squared	0.00965	0.85
Physical Activity Programme	-1.0786	-1.24
VLCD	-3.250	-1.68
Initial Weight-Change	0.525***	7.68
Full Programme Length	-0.112	-1.73
Full Programme Length -Squared	0.000730	1.27
Maintenance Phase	-2.594*	-2.74
Time from Weight-Loss Phase End	0.0549	0.76
Time from Weight-Loss Phase End Squared	-0.000484	-0.63

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

Following the univariate regressions, multivariate regression analysis was run predicting weight-change at the follow-up observations. Table 47 shows the multivariate meta-regression output for the 41 observations that were recorded across all studies at follow-up time points after the end of the initial weight-loss phases. Because the length of the weight-loss phase, whether the programme included a maintenance phase, and the time from the end of the weight-loss phase were already included in the model, the length of the full programme was removed from analysis due to concerns about potential collinearity.

The covariates included in the meta-regression explained 78.15% of the between-study variance in the outcome variable, weight-change from baseline, represented by an adjusted-R^2 statistic, which is a large proportion of the heterogeneity in outcomes. The I^2 statistic was 95.47%, which again suggested a high level of heterogeneity, whilst the joint covariate test produced a p-value of 0.000. Again, in Table 47 the regression results for the same regression equation without the observations taken from VLCD programmes.

Table 47: A Multivariate Meta-Regression on Weight-Change for all Observations Post Weight-Loss Phase

Variable	Coefficient (full model)	t-statistic (full model)	Coefficient (no-VLCD)	t-statistic (no-VLCD)
Age	0.392*	2.49	0.253	1.68
Female	2.266	1.70	1.327	1.06
Start Weight	0.109	1.80	0.0447	0.75
Weight Loss Phase	-0.513	-1.28	-0.368	-1.01
Weight Loss Phase Squared	0.0182	1.22	0.00948	0.69
Physical Activity Programme	-2.128*	-2.44	-3.290**	-3.67
VLCD	-3.513	-1.31		
Initial Weight Loss	0.304**	2.77	0.122	1.03
Maintenance Phase	-1.631	-1.41	-0.788	-0.70
Time from Weight-Loss Phase End	0.0555	0.81	0.0409	0.64
Time from Weight-Loss Phase End Squared	-0.000494	-0.71	-0.000319	-0.50
Constant	-31.49*	-2.42	-17.91	-1.42
N	41		36	

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

A number of variables had a significant impact on long-term weight-change outcomes in the full model. Each additional year of age resulted in 0.39kg less weight-loss from baseline, which is a large magnitude for each year of age. A greater starting weight predicted less weight-loss in the long-term, which is the opposite of the short-term effect where a greater starting weight predicted more weight-loss in the weight-loss phase. This may be due to heavier participants at baseline reverting to old habits in the long-term and regaining more weight-loss than their lighter peers. The programme offering physical activity sessions was also a significant predictor of more weight-loss. This could be due to habit formation and participants continuing to engage in physical activity in the long-term following programme completion.

A greater weight-loss inside the programme predicted significantly greater weight-loss from baseline in the long-term, with each additional kilogram of weight lost within the weight-loss phase predicting an estimated 0.3kg of weight-loss maintained at follow-up. However, this also means that those who lose most weight within the weight-loss phase gain more weight after the completion of the weight-loss phase as each kilogram lost within the weight-loss phase predicts less than a kilogram of maintained weight-loss. The programme including a maintenance phase predicted an additional 1.63kg of weight-loss maintenance.

The coefficient signs were identical for every variable in the no-VLCD model, although the coefficient size was smaller for all variables, except the physical activity, programme coefficient, which was larger in the no-VLCD model, predicting an additional 3.3kg of weight-loss compared to the additional 2.1kg predicted by the full model.

After the relationships between participants and programme characteristics, and weight-loss in the short-term, and weight-loss maintenance in the long-term were established, the final piece of meta-analysis was to establish a pattern of weight-regain over time following BWMs.

Figure 24: A Bubble Plot of Weight-Change Observations over Time

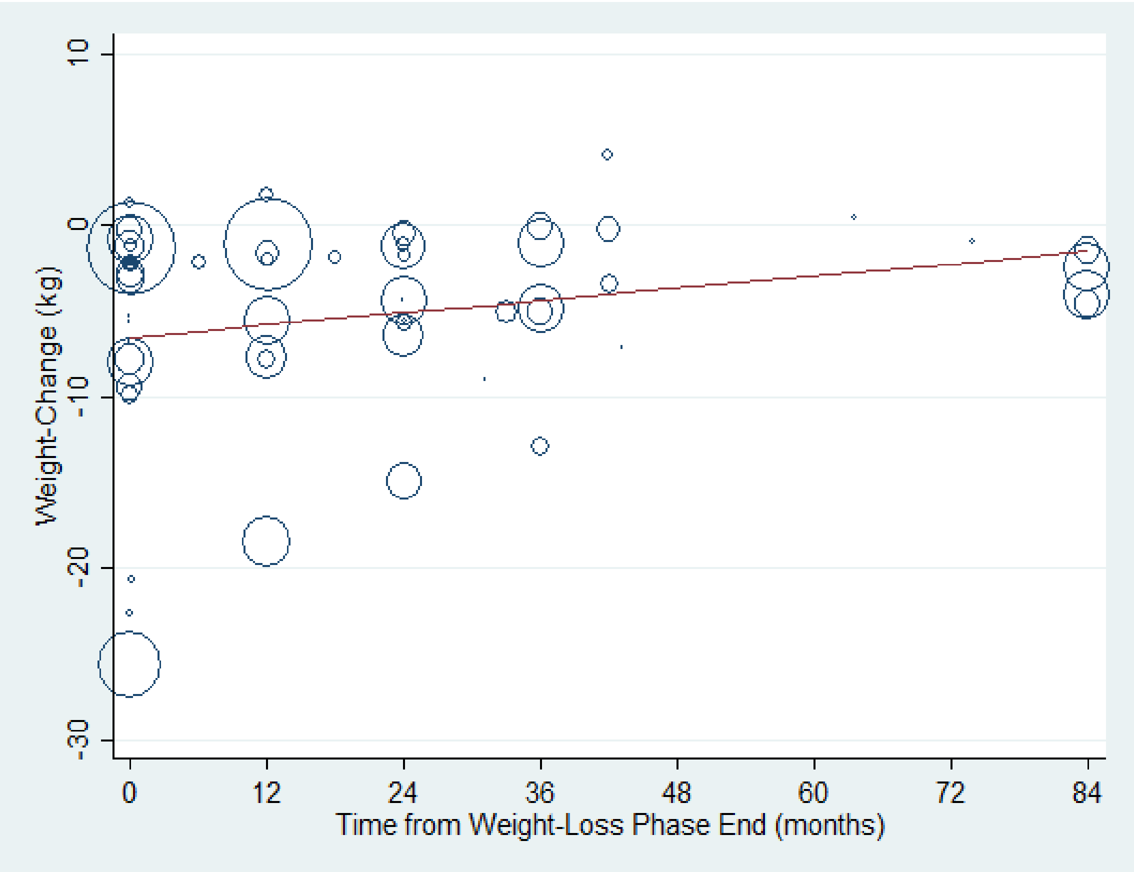


Figure 24 shows a bubble plot of observations across all programmes in a random effects meta-regression model predicting weight-change on time from the end of the weight-loss phase. In the bubble plot, the location of each circle illustrates the weight-change at each observation with the corresponding time-point the observation was recorded at. The size of each circle is proportional to the weight of the study observation in the meta-regression model. The line represents the predicted values of weight-change for each time-point, with the weight-loss experienced in the weight-loss phase being gradually regained over time.

The final meta-regression used all 60 observations to predict a weighted mean weight-change over time for participants across the 13 programmes. Again squared terms were included for the length of the weight-loss phase and the time from the end of the weight-loss phase. The length of the full programme was also removed from the equation. In the multivariate meta-regression, each additional month following the end of the programme initially predicted an additional 0.2kg of weight-regain, when controlling for all other variables, although this gain depreciated over time as the squared term produced a coefficient of -0.002kg. The regression produced an adjusted R^2 value of 80.04%, an I^2 value of 97.96%, and the joint covariate test had a p-value of 0.000. The full output is shown in Table 48.

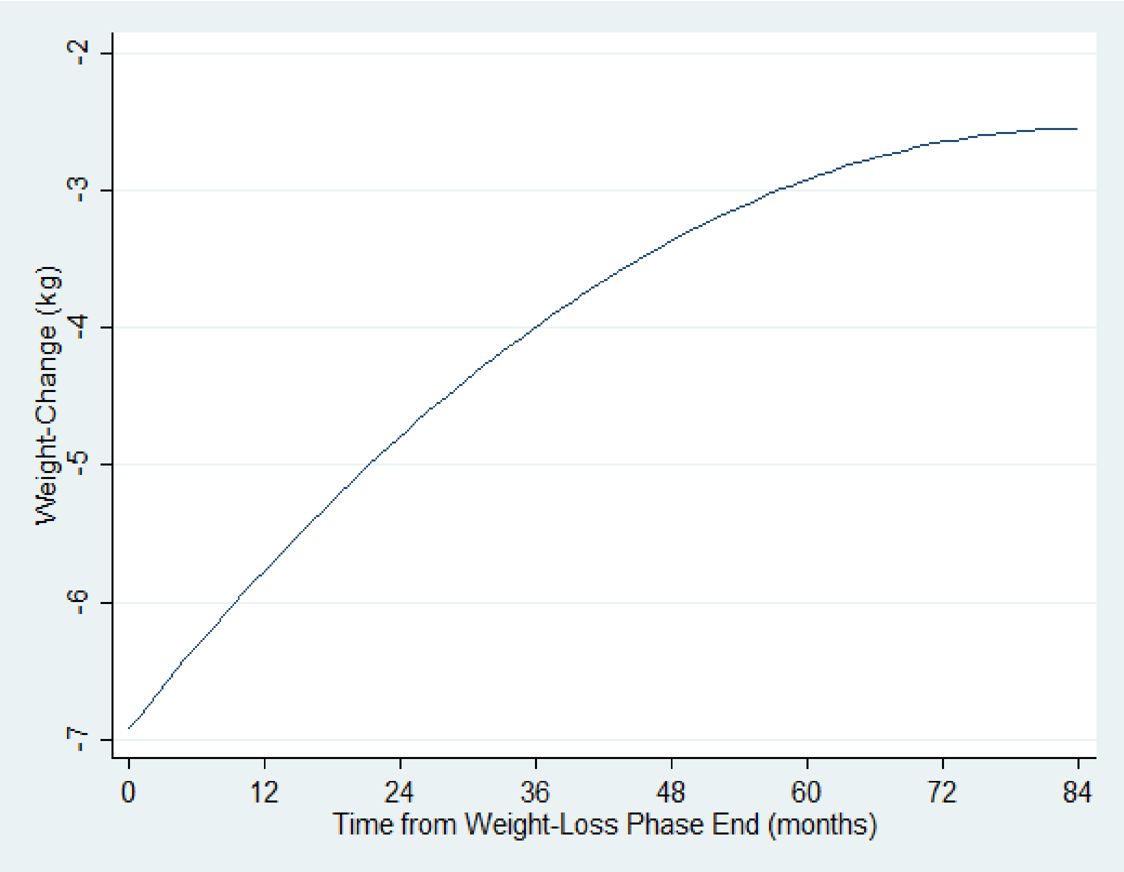
Table 48: Meta Regression Model Predicting Weight-Change including all Observations

Variable	Coefficient (full model)	t-statistic (full model)
Age	0.323*	2.20
Female	0.817	0.66
Start Weight	0.0328	0.60
Weight Loss Phase	-0.511	-1.71
Weight Loss Phase Squared	0.0196	1.70
Physical Activity Programme	-1.602	-1.85
VLCD	-2.053	-0.93
Initial Weight Loss	0.491***	4.52
Maintenance Phase	-0.679	-0.75
Time from Weight-Loss Phase End	0.199***	4.14
Time from Weight-Loss Phase End Squared	-0.00190**	-3.28
Constant	-21.75	-1.78
N	60	

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

Figure 25 illustrates the weight trajectory with weight regain slowing slightly over time. The graph shows participants are predicted to have lost around 7kg at the end of the weight-loss phase, and proceed to regain weight over time at a depreciating rate until weight-regain over the next 7 years. After 2 years, participants are expected to regain just over 2kg of weight-loss, whilst between 48 months and 84 months, there is only around a kilogram of weight-change.

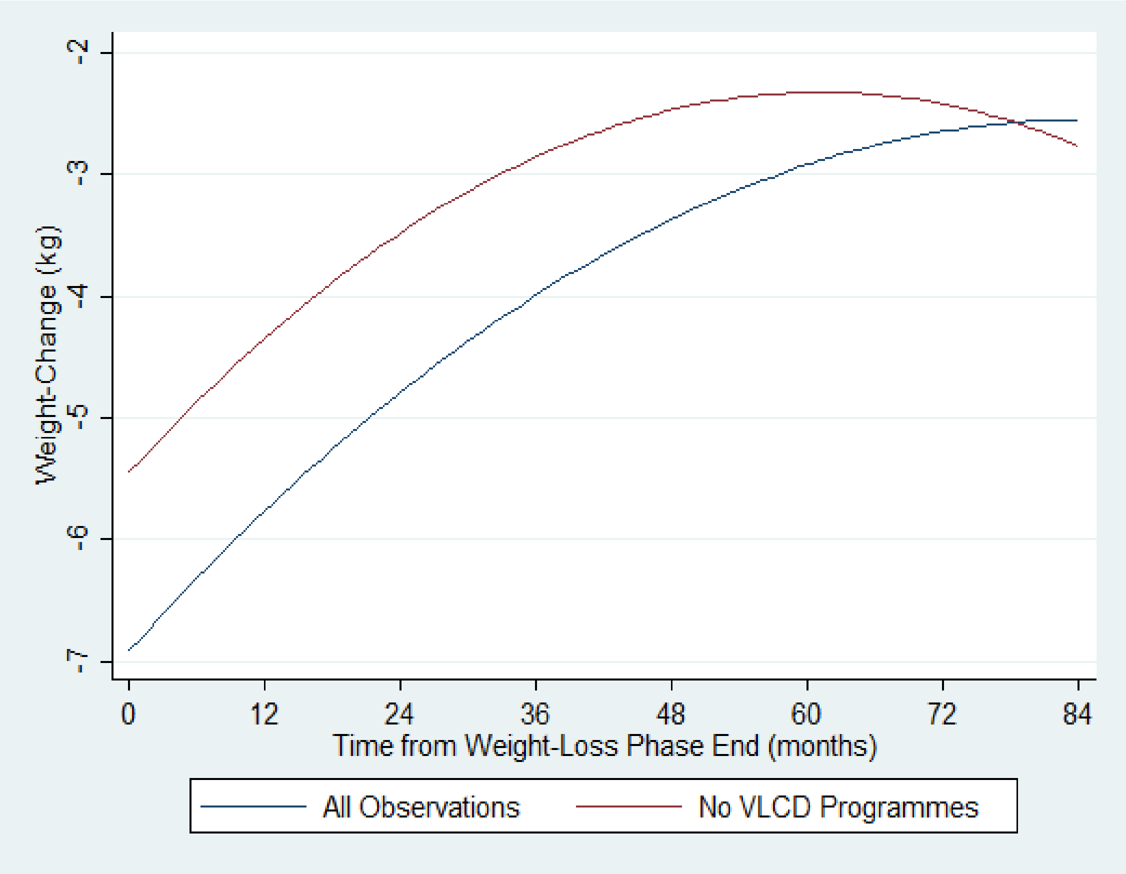
Figure 25: A Graph of Predicted Weight-Change from Baseline against Time from the End of the Weight-Loss Phase



As participants of the Slimming World programme do not engage in a VLCD, there is the question of whether VLCD programmes are comparable to the Slimming World programme. Because the purpose of this piece of work was to gain insight into weight-regain following behavioural weight-management programmes, in order to model weight-change following the Slimming World programme, the multi-variate regression analysis was run without the programmes with a VLCD included – Rolland et al. (2014), and the VLCD arm of Lantz et al. (2003). As the final follow-up observation in Lantz et al. (2003) includes both the VLCD and non-VLCD arm, this observation was still included in analysis. Therefore, a total of 8 observation were removed from analysis. The regression model used the same equation as the multivariate regression that used all observations, but without using VLCD as an explanatory variable, as VLCD programmes were not included and so the variable was redundant. The full regression output is shown in Appendix 25. The adjusted R^2 value fell to 70.77%, although the joint covariate test still produced a p-value of 0.000. The I^2 statistic was 96.12%. Each additional month from the end of the weight-loss phase predicted an additional 0.17kg of weight-gain, but the squared term producing a coefficient value of -0.0016kg, which are both close to the values predicted by the regression model with all 60 observations included.

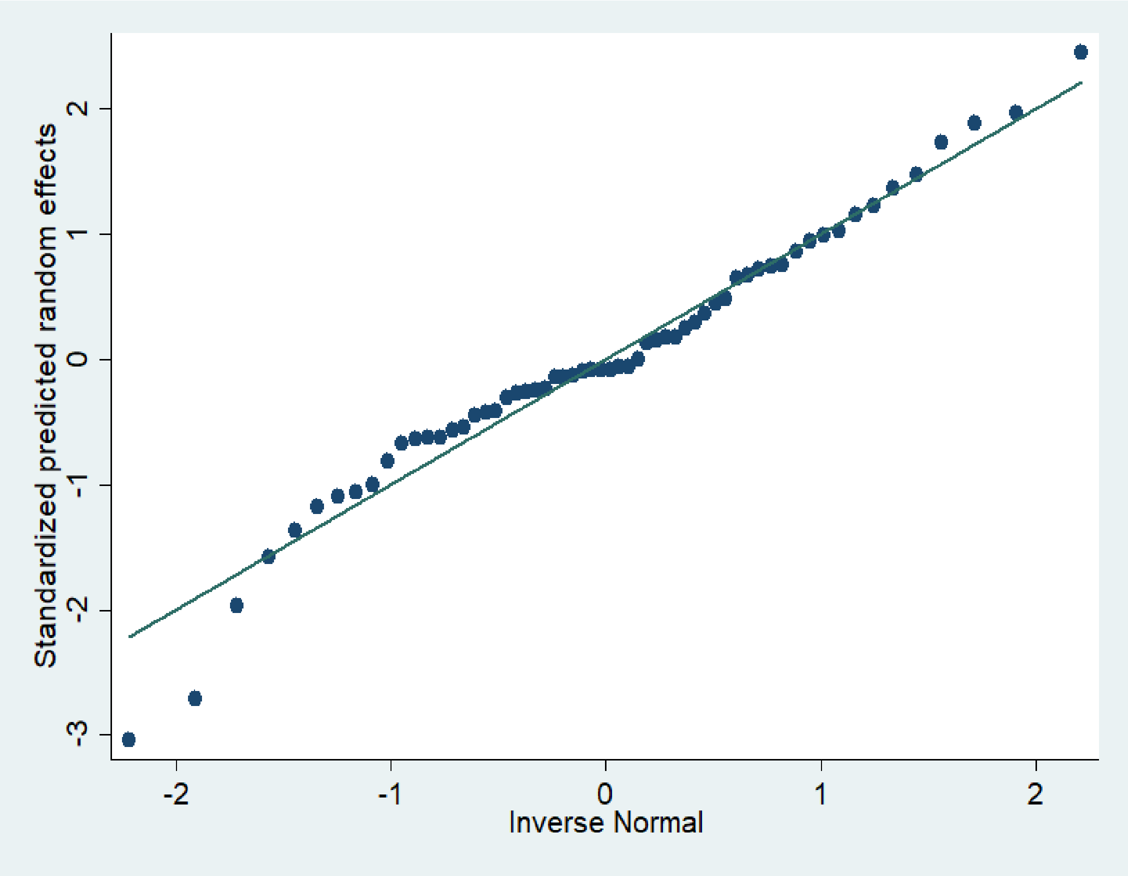
Figure 26, below, shows the predicted weight-trajectories from the end of the weight-loss phase for both models. Without the VLCD programmes, predicted weight-loss is around 1.5kg less, with weight being regained at a similar rate until around 4 years. At this point, the predicted weight-gain depreciates at a faster rate than the model using all observations predicts, until weight-loss is predicted from year 5 onwards. This is less plausible than the weight-trajectory predicted by the model using all observations, and is likely due to the low number of observations made over 5 years after the end of the weight-loss phases. Because removing VLCD programmes from the regression only made a small difference, and an indicator variable was included in the regression model for whether the observation was from a VLCD programme, the model with all observations was judged to be the better model to use to make predictions regarding weight-regain.

Figure 26: A Graph of Weight-Trajectories from the End of the Weight-Loss Phase using All Observations and without VLCD Programmes



Again, Q-Q plot was used to test whether there was a normal distribution of random effects. Figure 27 shows that the distribution again was close to normal revealing no issues with the meta-regression model.

Figure 27: Normal Probability Plot of Standardised Predicted Random Effects for all Observations



The final piece of analysis was to run the meta-regression without the age variable. The reason for this was that as ages were taken as an average of each study population, the range of ages between the studies was small, and as seen earlier, the coefficient value for each year of age in the meta regression model is large, which means that if an individual who is an extreme – either old or young, the accuracy of predictions will be limited. Table 49 shows the full model, which includes age, against a second model, which does not.

The no-age model had a higher I^2 to the full model, at 97.99%, and also had a p-value of 0.000 for the joint covariate test. The adjusted R^2 value was slightly lower at 78.22% compared with 80.04% in the full model, but this causes little concern regarding the negative effects of removing variables on the predictive ability of the model. The no-age model found that being female predicted more weight-loss than being male, which is the opposite of the prediction made in the full model.

The no-age model also estimated that a greater starting weight predicts greater long-term weight-loss, but only by 0.04kg per kilogram of weight, compared with 0.03kg less weight-loss in the full model. Another impact of removing age was that the impact of the length of the weight-loss phase was lessened, as each additional month predicted 0.21kg more weight loss compared with 0.51kg in the full model, with the squared term also producing a smaller coefficient value. The final notable difference was that when age was not controlled for, VLCD had an increased effect of weight-change.

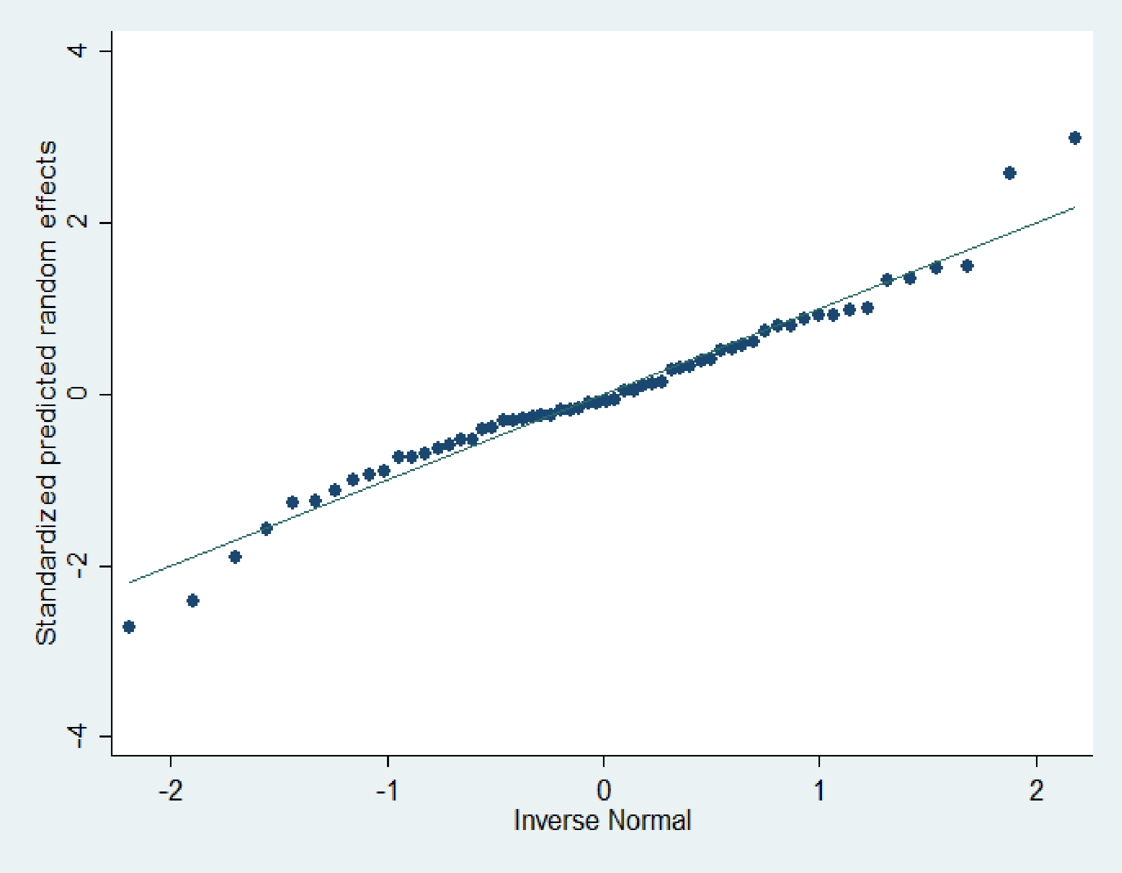
Table 49: Meta Regression Models Predicting Weight-Change including all Observations without Age Variable

Variable	Coefficient (no-age model)	t-statistic (no-age model)
Female	-0.478	-0.42
Start Weight	-0.0406	-0.90
Weight Loss Phase	-0.207	-0.75
Weight Loss Phase Squared	0.00783	0.73
Physical Activity Programme	-1.656	-1.84
VLCD	-3.316	-1.51
Initial Weight Loss	0.553***	5.06
Maintenance Phase	-0.618	-0.66
Time from Weight-Loss Phase End	0.194***	3.88
Time from Weight-Loss Phase End Squared	-0.00181**	-3.00
Constant	3.405	0.77
N	60	

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

Again, when checking the distribution of random effects for the no-age model, in Figure 28, there was little evidence from the Q-Q plot that the random effects were not normally distributed.

Figure 28: Normal Probability Plot of Standardised Predicted Random Effects for all Observations without Age and Gender



7.5 Discussion

This review adds to the current literature. It is the first meta-analysis of long-term outcomes at least 3-years post-baseline following participation in a behavioural weight-management programme. The main finding from the review was that participants regain weight following the end of the weight-loss phase in a non-linear fashion with the rate of weight-regain declining over time, and at least some weight-loss being maintained in the long-term. The review also found that despite maintenance programmes improving long-term weight-loss maintenance, participants in these programmes still regained weight after the initial weight-loss phase.

These results highlight the importance of considering future weight gain when evaluating the effectiveness of any weight-loss or lifestyle change intervention as even for those participants that attend maintenance phases and are engaged with follow-up, the effects are not sustained. The results are promising for policymakers – given that some weight-loss can be maintained in the long-term, even without maintenance programmes.

The meta-regression analysis found that individuals are expected to gain around half a kilogram per year following a behavioural weight-management programme. As a comparison to the general population, Mozaffarian et al. (2011) found a mean weight gain across a sample of over 100,000 individuals in the United States was 0.38kg per year. This is lower than the predicted weight-regain in this study, which is intuitive as weight regain is likely to be greater following a weight-loss programme due to individuals reverting to pre-intervention habits (Middleton et al., 2013). This trend is further illustrated by the non-linear pattern of weight regain after the weight-loss phase finishes with weight regain slowing over time.

The non-linear pattern of regain is useful for accurately estimating cost-effectiveness, as a non-linear pattern will provide a different estimation than if a linear regain is assumed. This is because if participants regain the majority of weight quickly, the health effects will not be as beneficial as if the weight regain is assumed to be linear, as the participants will spend less time with a lower bodyweight. This pattern shows that assuming a linear weight regain to baseline or a fixed annual weight regain is limiting, does not represent real world weight-change trends, and therefore may overestimate health benefits.

The strengths of the review are that it brings together a number of programmes from various countries, and combines them to show a trend which is intuitive – weight-management programme participants losing weight in the short-term with weight being regained at a declining rate. The explanatory variables managed to explain a large amount of the between-study variance in meta-regression analysis, and a large proportion of the participants were followed up in the long-run in each of the studies. Another strength of the review is that the participants in nine of the 13 programmes followed the same weight trajectory pattern – weight-loss in the short-term and slowly regaining over-time, with some weight-loss being maintained at the final follow-up at least 3-years from baseline. Of the four that did not fit this pattern, two programmes reported participants regaining weight to greater than baseline, with the other two reporting continued weight-loss after the initial weight-loss phase.

There were also some limitations to this review. The first is that 13 programmes is a small number, and therefore limits the statistical power of the analyses, which is a common problem with meta-analysis. As well as this, there was substantial variance between the studies in review, which makes drawing conclusions from the meta-regression analysis more uncertain. For example, some programmes were more intensive than others, but this was unobserved in the meta-regressions. Also, the retention rates by programmes in both the short-term and long-term varied between studies which can introduce selection bias. This is because those who responded to follow-up, and those who attended continued attending through maintenance phases, may have been more engaged with the programmes and therefore lost more weight or maintained more weight loss in the long-term. However, around half the participants that were attending at the end of the weight-loss phase had outcomes recorded at least 3-years from baseline which is a substantial proportion. Also, it may have been the case that those who did not respond had joined alternative programmes or continued managing their weight successfully without the help of a programme. The programme outcomes still illustrate what is possible from participants engaged with BWMs.

With the meta-regression analyses showing that some weight loss is maintained in the long-run for those who responded to follow-up, it is encouraging to both policymakers, and those wanting to lose weight, that lifestyle interventions can have lasting impacts on bodyweight and therefore health. For this thesis, this chapter has helped to describe the pattern of weight trajectories following the weight-loss phase which can be used to guide assumptions about weight-regain made in cost-effectiveness modelling where long-term outcomes are unknown.

In the cost-effectiveness model, after participants of the Slimming World programme have completed the initial intervention phase, the meta-regression model created in this chapter will be used to make individual level predictions of weight-change. By using this technique, projections of long-term weight-change will be more accurate as evidence from the literature will have been used to inform projections, rather than making general assumptions. Sensitivity and scenario analysis will be performed on the parameters in the regression model, as well as the method of implementing the regression model, in order to gain an understanding of the effect of changing assumptions on estimations of cost-effectiveness.

Chapter 8: Projections of Weight-Change Outside of the Slimming World Programme: Evidence from the ELSA Dataset and a Slimming World Follow-up Study

8.1 Introduction

The previous chapters explored the assumptions on long-term weight-trajectories following BMW programmes in economic modelling, and investigated evidence regarding weight-regain following behavioural weight-management programmes. Chapter 9 will utilise the Slimming World dataset and information found in previous chapters to predict long-term weight-trajectories for the Slimming World members, and test the assumptions made in other economic evaluations regarding long-term weight-change. However, to build these long-term weight-trajectories, two other sources of information were used: the ELSA, which was used to inform a background weight trajectory, and a follow-up study performed by Slimming World, which was used to inform the weight-trajectories of drop-outs. This enables a more informed and complete picture of weight-trajectories over a lifetime.

The purpose of cost-effectiveness modelling is to identify the impact of providing an intervention, considering both the effects and costs in the long-term. However, without information about what would happen to patients if the intervention was not provided, the findings regarding disease outcomes in the intervention group would be meaningless. To assess the impact of the intervention, outcomes must be compared to an alternative scenario in which no intervention, or a usual level of care, was provided. In randomised controlled trials, participants are randomised into either an intervention group or a control group, and the outcomes of each group are compared at the end of the intervention period in order to ascertain the effect of administering the intervention against the outcomes of the control group.

As well as using the ELSA dataset to create a background weight-trajectory for individuals in the intervention group, the background trajectory was applied to the control group. A cohort of individuals was created with identical baseline characteristics as the Slimming World cohort was created and applied weight-trajectories according to the trajectories seen in the general English population. The creation of an artificial control group enables a comparison between the two groups to identify the difference between the outcomes of the intervention group and what would have happened to a similar group of patients if they had not received any intervention.

As well as assessing the ELSA dataset to understand background weight-trajectories in the United Kingdom, this chapter seeks to understand weight-change trends for participants who leave the Slimming World programme. A problem with assessing behavioural weight-management programmes is that they are generally unable to observe weight-change for individuals who leave the programmes. By analysing a follow-up study Slimming World performed on their own members, this chapter seeks to identify weight-change patterns following attending the Slimming World programme, and use regression models to predict weight-change for individuals who leave the programme in cost-effective modelling.

The Slimming World follow-up study was undertaken with the aim of measuring the body weights of a small sample of members who joined the Slimming World programme around 3 years prior. The follow-up study therefore provides valuable insight into the potential weight trajectories of Slimming World members after they leave the programme.

This chapter will describe the details of both the ELSA and the follow-up study, and the methods used to create a background weight-trajectories and weight-change between leaving the Slimming World programme and follow-up. The baseline data for the respondents will then be presented, as well as outcome data collected at attendances and at follow-up. Following this, the data will be analysed using regression techniques to review the different weight outcomes according to individual characteristics, and make predictions regarding follow-up weight-change. By analysing these two datasets, patterns of weight-change of outside of the Slimming World programme, and the meta-regression of long-term weight-change in Chapter 6, will be identified, for use in cost-effectiveness modelling. This chapter therefore aims to fill gaps in knowledge by answering the questions:

1) What is the weight-trajectory for people in England who do not receive an intervention?
2) What is the weight-trajectory of people who leave a behavioural weight-management programme?

8.2 Methods

8.2.1 The English Longitudinal Study of Ageing

The English Longitudinal Study of Ageing is a study of a number of cohorts of people from England aged 50 or older at the first assessment (ELSA, 2019). The members in the sample were taken from respondents to the HSE and are therefore representative of a general English population. Three cohorts were included initially – a cohort taken from the 1998 HSE, a 1999 HSE cohort and a 2001 HSE cohort.

The information recorded in the HSE for the three cohorts were included in the ELSA data and labelled as 'wave 0' data, and used as the baseline data for all participants. Following 'wave 0', 'wave 1' interviews took place in 2002 for all participants. The participants were interviewed every 2 years after wave 1, with 9 waves in total as of March 2019. The interviews included nurse visits in waves 2, 4, 6 and 8. Participant body-weight was measured by nurses in waves 2, 4 and 6. In wave 8, weight measurements were carried out by the interviewers. New participants were introduced in waves 3, 4, 6, 7 and 9 to maintain an appropriate sample size, although only participants that joined in wave 0 were included in this analysis. This was so each participant would have a similar timeframe for their weight-trajectory, and so data recorded for the baseline variables in the HSE was in an identical format for each member of the sample.

ELSA was chosen as appropriate data source for background weight trajectory for a number of reasons. Firstly, as the ELSA was a longitudinal study, the same participants were being tracked over time which eliminates any potential discrepancies between the samples each year that may be present in cross-sectional data. By using longitudinal data, there is less uncertainty regarding weight-change over time and the weight-change can more easily be attributed to societal trends and the aging process. The second reason was that weights were measured by nurses and so were assumed to be accurate and not subject to any biases that are common with self-reported weights (Robinson and Oldham, 2016). The third reason was that the ELSA participants are aged 50 and above, and as they are recruited from the HSE, weight measurements have the potential to be available from ELSA participants at age 45, which is appropriate for the Slimming World cohort as the mean age in the cohort is in the 40s.

8.2.2.1 The ELSA Dataset

A total of 18,434 individuals were involved in wave 0 of the ELSA, with 11,205 of these individuals being core sample members that included in follow-up. Of these, 796 members did not have a weight recorded at baseline and so were removed from analysis as weight-change was recorded against weight at baseline. This left a total of 10,409 individuals from the ELSA that were included in the data analysis. This sample of individuals was compared with the Slimming World dataset, but it was decided to not match the two samples. This decision was made as a sample based on all available data in the ELSA dataset would be more informative. One reason for this was as each individual in the ELSA dataset is only followed up for 4 separate weight-measurements, with the mean time from baseline to the final measurement being 16.9 years. As weight-trajectories are required for a lifetime time-horizon, and these trajectories carry a large amount of uncertainty, it was decided that using all available data from the population of individuals in the ELSA dataset was most appropriate.

The majority of variables were taken at baseline from HSE data, with weight and age being recorded at waves 2, 4, 6 and 8. Table 50 shows each of the baseline variables in the dataset, with a note of the prevalence of missing data for each of the variables. Apart from household income, over 97% of sample members had data for all variables at baseline.

Table 50: Missing Data at Baseline

Variable	Missing Number	Missing Percentage (%)
Gender	0	0.00
Age	25	0.24
Weight	0	0.00
BMI	288	2.77
Top Qualification	1	0.01
Employed/Self-Employed	210	2.02
Equivalent Household Income	1,419	13.63

Married and Living with Partner	3	0.03
Number of Children Living at Home	0	0.00
Self-Assessed Health	2	0.02

Table 51 shows a summary of the age, weight and BMI for core members from wave 0. Participants were on average 62.39 years old, which is greater than the mean age of the Slimming World cohort, as the purpose of the analysis is to build future weight trajectories as the individuals in the Slimming World cohort age. The minimum age was 45, as even though the minimum age to be included in the ELSA data was 50, some participants were younger when they were first included in HSE data, with a total of 914 (8.8%) of the ELSA participants were under 50 at baseline. The maximum age recorded by ELSA was age 90. Participants were 75.75kg on average, which corresponded to a BMI of 27.59kg/m^2 – which is classed as overweight. In the sample, 70.3% of respondents had a BMI of over 25kg/m^2 at baseline. A total of 2,566 (25.4%) participants had a BMI of 30kg/m^2 or higher at baseline.

Table 51: A Summary of Key Variables at Baseline

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Age (years)	10384	62.17	10.13	45	90
Weight (kg)	10409	75.75	15.03	33.00	162.10
BMI (kg/m^2)	10121	27.59	4.57	14.81	55.98

In the sample, 5,688 (54.7%) core members were female. At baseline, 7,090 (68.13%) core sample members were married and living with partners. Seven-hundred and thirty seven (7.1%) of core members were living with at least one child between the ages of two and 15 at baseline.

Half of members (50.1%) had earnings from employment or self-employment at baseline. Mean equalised household income amongst the 8,990 members who had data available was £20,488.54 per annum. Table 52 shows a summary of the highest qualifications obtained by individuals in the sample. Over half of members had some form of qualification with over 20% having some form of higher education.

Table 52: Frequencies of Top Qualification Achieved

Top Qualification	Number	Percentage (%)
No Qualifications	4,551	43.7
Foreign/Other	840	8.1
Certificate of Secondary Education equivalent	500	4.8
O-Level equivalent	1,649	15.8
A-Level equivalent	601	5.8
Higher Education below Degree	1,140	11.0
Degree or equivalent	1,127	10.8

Participants at baseline were asked to rate their general health on a scale of very bad to very good. Table 53, below, shows the distribution of responses. Over a quarter of members reported being in 'very good' health at baseline whilst under 10% considered themselves to be in either bad or very bad health.

Table 53: The Self-Assessed General Health of Respondents

General Health Response	Number	Percentage (%)
Very Good	2,944	28.3
Good	4,066	39.7
Fair	2,525	24.3
Bad	693	6.7
Very Bad	179	1.7

8.2.2.2 Analysis of the ELSA Dataset

Before reviewing any weight outcome data, any potential outliers for weight measurements after baseline were identified. To ensure obvious errors were removed, participants who had either greater than a 50% decrease in weight or a 100% increase in weight were set to missing. As a result, a total of four weight observations across the five waves were set to missing.

As not all weight data at each wave were collected at the same time, the times between each wave measurement for each person were created by subtracting each participants age at wave 0 by the age of each participant at subsequent waves. These times were rounded to the nearest year as age was recorded as age at last birthday. A further issue with ELSA is that the age of the participant is not recorded after the age of 90. Therefore, in the data analysis, individuals who were above 90 had missing data for age. Because of the time between weight measurements was recorded as the difference in age between the two measurements, the time of measurement was also missing from the dataset.

The first step of regression analysis was to perform univariate regressions on weight-change, controlling for baseline weight, time and time-squared, which was included due to the non-linear relationship between weight-change and time. This was to identify the influence of each explanatory variable in turn, whilst holding these variables constant. Following univariate analysis, a multivariate regression model was built to predict weight-change for the full sample.

As the purpose of this modelling was to create a background weight-trajectory to be used by those retrospectively assessing weight-management programmes, and not all these variables may be available, a more practical model was created to make predictions about long-term weight-trajectories. This model was built using only readily available variables that BWMs would routinely collect.

Rather than using time from baseline as a predictor of weight-change, the participants' age at the weight observation was used as a predictor instead. This was in order to distinguish between the varying weight-trajectories between different ages, as time does not account for varying weight-change patterns at different ages. As well as this, the longest time period between any two weight observations for a single individual was 22 years. As models will often analyse a period of time longer than 22 years, using baseline age and age at the weight observation is more useful.

8.2.2.3 Creating a Background Weight-Trajectory for the Slimming World Cohort

As the Slimming World dataset also had information about the income and education levels of members, these variables were included in the basic model, as additional variables. Income and education levels were chosen to be included in the model as they are included in projections of weight-loss within the Slimming World programme.

To be able to successfully map the variables concerning income and education levels from the ELSA data to the Slimming World cohort, the variables in the ELSA dataset were adjusted. As the income variable in the Slimming World data was IMD quintiles, equalivalised household income was converted into quintiles, with the assumption being that the sample of ELSA data was representative of the general population, and that the quintiles created in the ELSA data were close to the true quintiles for the general population.

The Slimming World data were again separated into quintiles for Education IMD, whilst in the ELSA data qualifications were ranked from 1-7. To be able to map the 7 ELSA qualification categories to the education IMD quintiles, assumptions regarding the quintile of each class were made. It was assumed that those with no qualifications were in the bottom quintile as these individuals are the most deprived in terms of education. Those with 'foreign'/'other' qualifications and secondary education certificates were assumed to be in the second bottom quintile as in the ELSA data, these were lowest two ELSA categories, and neither were represented by a large proportion of individuals. The middle quintile was assumed to consist of O-level completers. The second highest quintile included A-level completers and non-degree higher education, whilst the top quintile consisted of individuals with higher education degrees. By grouping each type of individual as such, each category had at least 10% of the full sample and so was reasonably well represented.

The model was then applied to a random sample of 10,000 individuals from the Slimming World dataset, and mean weight was plotted against age. As the mean age in the cohort was 43, all individuals were assumed to be 43 at baseline. Each age from the age of 44 was then used as the age at the new observation up to the age of 100. The predicted weight-change each year was then added to the baseline weight to create a mean weight for the cohort each year.

8.2.3 The Slimming World Follow-up Study

As considering the long-term effects of weight-management programmes is vital to evaluating the effectiveness of the programme, Slimming World sent out surveys to members with the primary aim of establishing the most effective method of engaging individuals to assess their long-term weight-management outcomes. A number of secondary aims were also included such as collecting weight outcomes 3 years from the individual's sign-up, why and how individuals may or may not continue their behavioural change and the long-term impacts on their family and health. The members selected to be sent the survey were

8,000 members from the Nottingham, Derbyshire and Coventry areas that joined between January and June in 2012. As an incentive, those who completed the survey were entered into a prize draw.

The Slimming World dataset contained a total of 415 respondents. Of these 293 survey respondents were matched via individual membership IDs to the full Slimming World dataset. Seven respondents were pregnant or had a baby in the last six months and so were excluded due to the effect of pregnancy on bodyweight. A further four individuals who did not have a follow-up weight recorded were also removed. Finally, one participant who left Slimming World before the follow-up, was weighed at the start of the programme, but was not weighed at subsequent attendances after beginning Slimming World was removed from analysis, due to uncertainty about the individual's weight-change within the programme. This led to a total of 281 Slimming World members remaining for analysis. Of the 281 members in the dataset, 51 were still members of the Slimming World programme, with 230 no longer attending classes at the time of follow-up.

Table 54 shows the prevalence of missing data amongst the variables in the follow-up dataset. The amount of missing data was small, except for target weight, with only 63.8% of participants having a target recorded, which is likely because not all Slimming World consultants record the targets members set in the database.

Table 54: Missing Data in each Variable

Variable	Number of Missing Observations	Proportion of Missing Observations (%)
Age	4	0.7
Gender	0	0.0
Current Member	0	0.0
Start Weight	0	0.0
Target Weight	102	36.2
Height	1	0.4
Time in Slimming World Programme	0	0.0
Follow-up Time from Baseline	0	0.0

The vast majority of respondents in the dataset were women – a total of 264 (94.0%), compared with 17 men. The mean age of respondents was 46.5 years at the recorded start date, with the range being 18.2 to 66.0 years of age. Of the remaining 281 respondents, 230 (81.9%) had left the Slimming World programme, with the remaining 51 still attending classes at the time of follow-up. Twenty-three (8.2%) of the participants joined Slimming World through the Slimming World on Referral (SWoR) programme.

Table 55 shows a summary of start weight, the corresponding start BMI as well as target weight and BMI. The mean start weight was 91.5kg with a range of over 125kg. At baseline, the majority of participants were obese (65.7%) with the average individual having a BMI of 33.7kg/m^2. This is compared with the full dataset in which the mean start weight was 90.5kg, the mean BMI was 33.3kg/m^2, and the proportion of individuals with obesity was 66.7%. Participants on average set a target weight-loss of 20.9kg, which corresponded to a target BMI of 26.1kg/m^2 – which is still regarded as overweight, but close to healthy weight.

Table 55: Baseline Weight, BMI and Targets for All Respondents

Variable	n	Mean	SD	Min	Max
Start Weight (kg)	281	91.49	19.64	53.98	179.40
Start BMI (kg/m^2)	280	33.70	6.37	22.50	56.62
Target Weight (kg)	180	70.59	12.13	47.57	114.16
Target BMI (kg/m^2)	179	26.05	3.69	19.85	38.87

This analysis intended to assess the outcomes of these respondents. The outcomes of the participants were assessed before building regression models to predict weight-change for those who left the Slimming World programme. Ordinary least squares regression was the chosen regression technique as weight-change was normally distributed and a linear model was most appropriate.

The first stage of analysis of the Slimming World follow-up study was to perform a series of univariate regressions predicting weight-change after participants dropped out of the Slimming World programme, whilst controlling for start weight, weight-loss in the Slimming World programme, and the time between leaving the programme and follow-up, as well as a squared term for the time to follow-up. Because the purpose of this analysis was to identify weight-change trajectories outside of the Slimming World programme, only the 230 individuals who had left the Slimming World programme prior to follow-up were included. Following the univariate analysis, multivariate regression analysis was performed and used to predict weight-change following the Slimming World intervention for a random sample of 10,000 Slimming World members from the full dataset.

8.3 Results

8.3.1 The ELSA Dataset

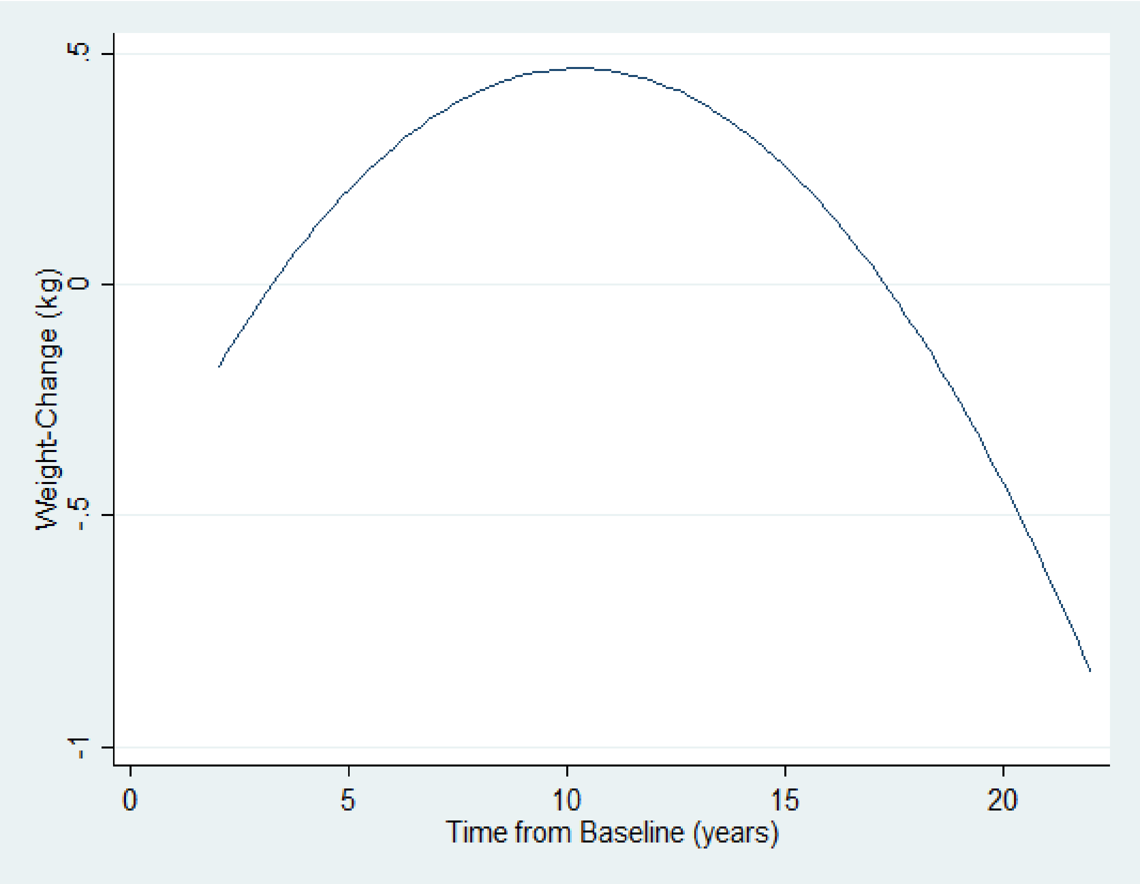
Table 56, below, shows a summary of weight-change across the sample at each wave. The number of observations at each wave declined each wave, which is expected in long-term follow-up, but meaningful sample sizes were maintained in each wave. At wave 2, two-thirds of participants were measured whilst at wave 8, which was around 17 years from baseline, a third of individuals responded to follow-up. Across the whole sample, participants gained weight until wave 4 and lost weight afterwards.

Table 56: Weight-Change from Baseline at each Wave of Observations

Wave	Observations	N (%)	Mean Time to Wave Measurement (years)	Mean Weight-Change from Baseline (kg)
Wave 2	6,943	66.7	5.16	0.199
Wave 4	5,131	49.3	9.07	0.527
Wave 6	4,332	41.6	12.86	0.101
Wave 8	3,409	32.8	16.91	-0.331

The trend is again shown in Figure 29, where weight-change from baseline is plotted against time from baseline. It can be seen that over the 20-year period, sample members on average reached a peak weight-gain around 10-years after baseline before losing weight from there onwards. However, Figure 29 describes an average weight-change from baseline for all ages. To investigate weight-change as people age, regression methods will be used to make predictions regarding weight-change for participants of a given age.

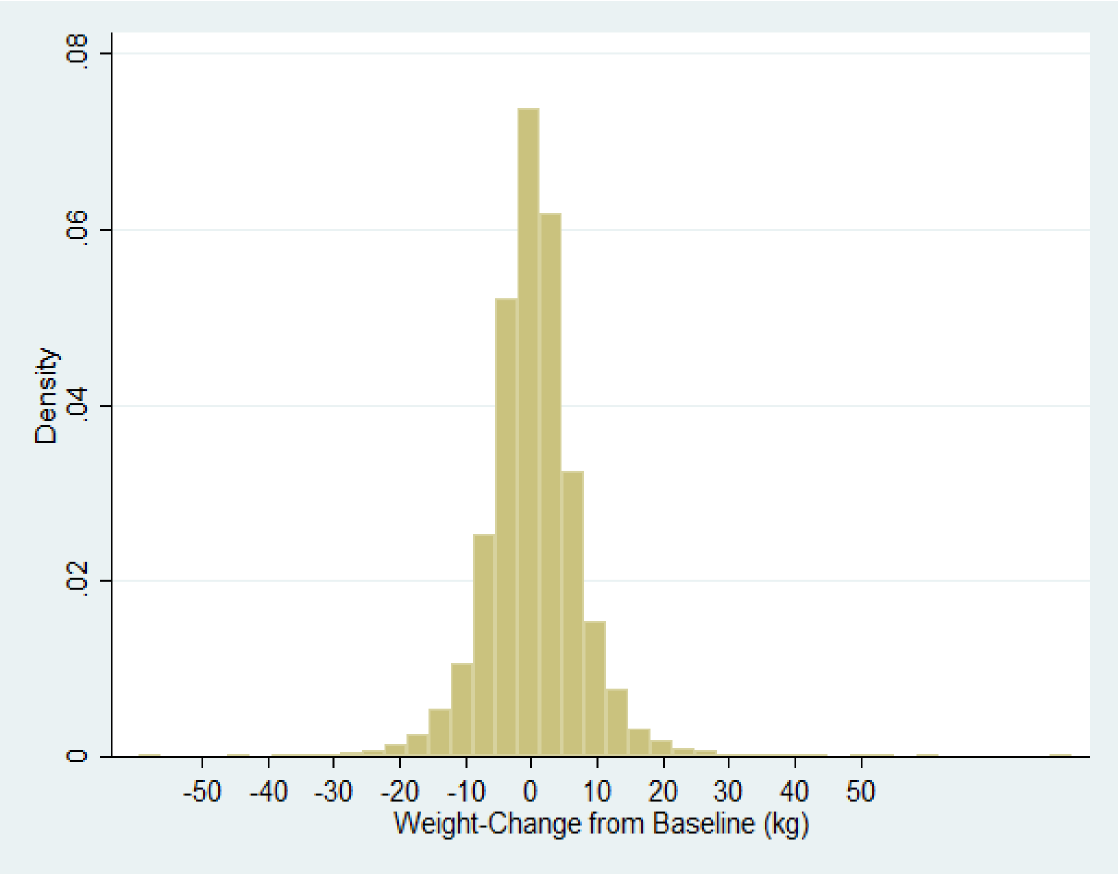
Figure 29: Weight-Change over Time for the Sample



8.3.1.1 Predicting Background Weight-Trajectories using the ELSA Dataset

Before building a regression model, the distribution of weight-change was plotted in a histogram in Figure 30. After baseline, a total of 19,815 weight observations were made for the core members from wave 0 between waves 2 and 8. A close to normal distribution of weight change was identified with a mean of 0.17kg skewness of 0.217. Because of this distribution, OLS regression was chosen to predict weight-change from baseline over time.

Figure 30: A Histogram of Weight-Change from Baseline



Univariate regression analysis found all variables other than self-assessed health were significant predictors of weight-change at the 5% level, as seen in Table 57. Being female, being older and having a greater BMI at baseline predicted more weight-loss/less weight-gain, whilst being more educated, being employed, having a greater household income, being married and having children were predictors of less weight-loss/more weight-gain over time.

Table 57: Univariate Regressions Predicting Weight-Change

Variable	Coefficient	t-statistic
Gender (female=0, male=1)	0.396***	3.59
Age at Baseline (years)	-0.205***	-35.12
Weight at Baseline (kg)	-0.0308***	-9.03
Top Qualification (least qualified=0 -most qualified=7)	-0.0511*	-2.31
Equivalent Household Income (£000s)	0.0108***	4.38
Employed/Self-Employed (no=0, yes=1)	2.389***	23.43
Married and Living with Partner (no=0, yes=1)	0.225*	2.01
Number of Children Living at Home	1.157***	10.35
Self-Assessed Health (very bad=0)	0.0353	0.63
Time from Baseline (years)	0.193***	3.56
Time from Baseline - Squared (years)	-0.00943***	-3.75

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

A multivariate regression model was built using the variables in Table 57. All explanatory variables were significant predictors of weight-change other than equivalent household income, the number of children, self-assessed health, and time from baseline. The output from the final regression model is shown in Table 58, below.

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Table 58: Multivariate Regression Model Predicting Weight-Change

Variable	Coefficient	t-statistic
Male	0.504***	4.34
Baseline Age	-0.198***	-24.23
Baseline Weight	-0.0471***	-12.02
Top Qualification	0.154***	6.11
Equivalent Household Income	-0.00346	-1.15
Employed	0.569***	4.08
Married	-0.306**	-2.59
Number of Children	0.186	1.53
Self-Assessed Health	0.0813	1.35
Time	0.0877	1.56
Time Squared	-0.00839**	-3.24
Constant	15.117***	20.33
N	17,166	

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

Being older, having a higher weight at baseline, having a higher level of qualification and being married all predicted more weight-loss, or less weight-gain, whilst having earnings from employment or self-employment at baseline predicted less weight-loss or more weight-gain. As in the univariate regressions, the time and time-squared variables tell us participants on average gain weight initially and this weight-gain slows until individuals begin to lose weight. The regression model explained 6.9% of heterogeneity in outcomes, meaning that the predictive power of the model was fairly low. However, the regression output is still able to produce predictions of weight-change as individual's age, and build a background weight-trajectory for use in modelling.

The next step of analysis was to establish a basic multivariate regression model to predict weight-change, using only readily available variables. This model, shown in Table 59, included only five predictors of weight-change over time: gender, age at baseline, baseline weight, and the age at the weight-change observation, with age at the weight-change observation squared also being included.

Table 59: The Basic Model of Predicting Weight-Change from Baseline over Time

Variable	Coefficient	t-statistic
Male	0.467***	4.38
Age at Baseline	-0.095***	-8.37
Baseline Weight	-0.0504***	-13.74
Age at New Observation	0.496***	6.03
Age at New Observation	-0.00431***	-7.23
Constant	-3.768***	-1.29
N	19,482	

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

All 5 variables were significant at the 1% level. Being male predicted less weight-loss, whilst being older and having a greater starting weight at baseline predicting more weight-loss. Each additional year predicted weight gain, but this weight-gain slowed over time, due to the squared term for age at new observation. This meant that while individuals were younger, their weight increased but this rate of increase slows over time and eventually weight-loss occurs.

8.3.1.2 Creating a Background Weight-Trajectory for the Slimming World Cohort

The final multivariate regression model was the model created with the purpose of predicting weight-change for use inside the cost-effectiveness model. The output from the regression model for making predictions regarding weight-trajectories over time for the Slimming World cohort is shown in Table 60, below.

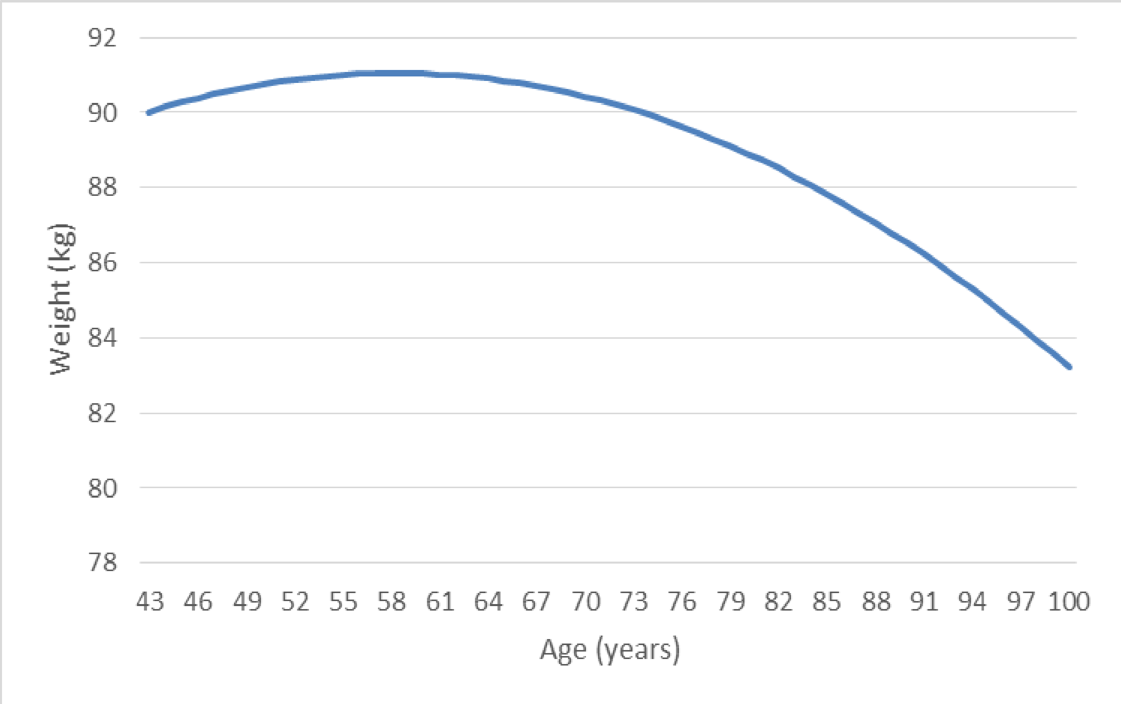
Table 60: Regression Model to Predict a Background Weight-Trajectory

Variable	Coefficient	t-statistic
Male	0.518***	4.53
Age at Baseline	-0.111***	-8.96
Baseline Weight	-0.0482***	-12.41
Education Quintile	-0.219***	-5.52
Income Quintile	-0.0685	-1.60
Age at New Observation	0.523***	6.01
Age at New Observation	-0.00449***	-7.12
Constant	-3.495	-1.13
N	17,175	

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

Figure 31 shows the model's projection of a random sample of 10,000 individuals from the Slimming World cohort. The model predicts that from the age of 43, on average individuals in the cohort gain weight at a declining rate until they reach peak weight at age 58. After this, the individuals lose weight on average at an increasing rate for the remainder of the extrapolated time period.

Figure 31: Predicted Mean Weight over Time for the Slimming World Cohort



8.3.2 The Slimming World Follow-up Study

As mentioned previously, 51 participants were still attending Slimming World classes at the time of follow-up, with 230 respondents having left the programme before the follow-up. The mean participant attended Slimming World classes for just over a year, with those who dropped out before the follow-up attending for an average of 8.1 months. The mean time between the last attendance and follow-up was 2 years and 4.2 months.

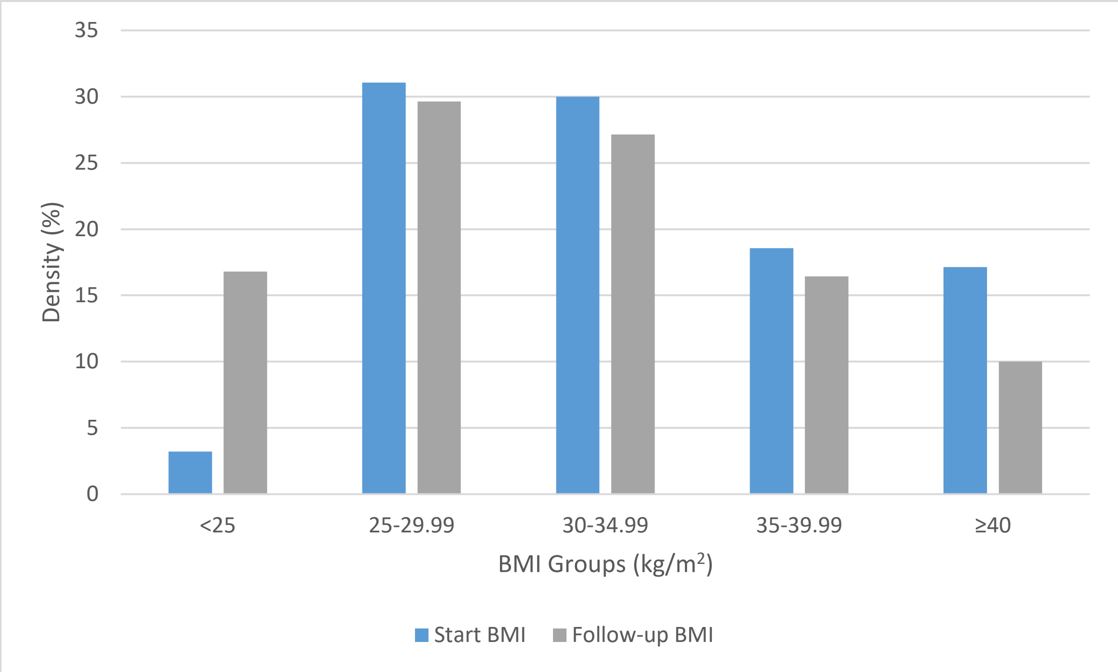
The mean weight-loss in the Slimming World programme was 7.58kg. A total of 259 (92.22%) of respondents lost weight whilst they were attending Slimming World classes, with 158 (56.2%) losing at least 5% of their baseline bodyweight. Of the 180 participants that had recorded targets, 19 (10.56%) of them were at, or below, their initial target weight, at the time of follow-up. A total of 153 (54.45%) of participants had maintained a weight-loss of 5% or more at the time of follow-up. The respondents that were members of Slimming World at the time of follow-up had lost an average of 14.96kg – over three times the average weight-loss of 4.61kg for those who dropped out of the programme. Table 61 shows a summary of the time frames and weight change outcomes for respondents to the follow-up survey.

Table 61: A Summary of Outcomes for All Respondents

Variable	n	Mean	SD	Min	Max
Time in Programme (months)	281	13.24	13.24	0	40.27
Time from last attendance to follow-up (months)	281	23.09	13.22	0	41.68
Weight-Change in the Slimming World Programme (kg)	281	-7.58	8.49	-71.89	13.38
Weight-Change from Start to Follow-up (kg)	281	-6.49	10.42	-73.48	15.88
Weight-Change from Drop-out to Follow-up (kg)	230	1.34	7.79	-56.69	29.94

When reviewing BMI groups, Figure 32 shows the proportion of participants in the top four BMI groups falling between baseline and follow-up, with the proportion of respondents in the healthy BMI group increasing substantially from 9 to 47 (3.21% to 16.79%). At baseline, 184 (65.7%) of those surveyed were obese, which fell to 150 (53.6%) at the time of follow-up.

Figure 32: A Histogram of BMI Groups at Baseline and Follow-up



All 23 of the participants who joined via the Slimming World on Referral programme had dropped out at the time of follow-up, with a mean time in the programme of 4.1 months. Referral members lost an average of 5.4kg in the programme, and a further 2.0kg between leaving the programme and follow-up. Twenty-one (91.3%) of the SWoR members lost weight inside the programme, with 14 (60.9%) gaining weight between leaving the Slimming World programme and follow-up.

The mean weight-loss amongst drop-outs within the Slimming World programme was 5.9kg. Participants who dropped out of the programme had regained an average of 1.3kg between the time of their final attendance and follow-up. Of the 230 participants that dropped out before follow-up, 149 (64.8%) of them gained weight after leaving the programme. Those who gained weight gained an average of 5.2kg, whilst those who lost weight lost an average of 5.77kg over the average follow-up period of 18.4 months.

8.3.2.1 Regression Analysis of the Slimming World Follow-up Data

The first step of analysing the drivers of weight change after the Slimming World programme was to perform univariate regression analysis. Table 62 shows a summary of the univariate regressions outputs.

Table 62: Univariate Regressions Predicting Weight Change between Baseline and Follow-up

Explanatory Variable	Coefficient	t-statistic
Age (years)	-0.0879	-1.89
Gender (female=0, 1=male)	-7.861**	-2.93
Start Weight (kg)	-0.0400	-1.46
Referral Member	-3.347*	-1.97
Target Weight Change (kg)	0.0411	0.49
Weight Change in the Slimming World Programme (kg)	-0.356***	-3.27
Time in the Slimming World Programme (months)	0.406	1.40
Time from leaving the SW Programme to Follow-up (months)	0.0801	-0.27
Time from leaving the SW Programme to Follow-up Squared (months)	-0.00193	-0.30

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

The univariate regressions revealed that three variables were significant predictors of weight-change between leaving the Slimming World programme and follow-up. Being male and joining the Slimming World programme via referral were both significant predictors of greater weight-loss at follow-up. Losing more weight within the Slimming World programme predicted an additional 0.356kg of regain for every kilogram lost within the programme. This implies that whilst those who lose more weight gain more after leaving the programme, they still maintain some of their weight-loss. The univariate regression predicted that each month outside of the programme predicting 0.08kg of weight-regain and after the first month this weight-regain came at a declining rate.

The primary aim of the analysis was to run multi-variate regressions using the variables in the univariate regressions, again with weight-change between leaving the programme and follow-up as the dependant variable. Gender was not included in the multi-variate equation as even though the effect size was significant, only 9 of the 230 individuals were male, and the sample size was determined to be too small to be a meaningful estimate of the effect of gender. Due to target weight change being an insignificant predictor of follow-up weight change, as well as reducing the sample size, the variable was also dropped from analysis. Finally, because all participants were followed up 3-years from baseline, collinearity was present between the time in the Slimming World programme variable and time from the end of the programme to follow-up variable. Therefore, the time in the Slimming World programme variable was not included in the multivariate model. The output from the multivariate model is shown in Table 63, below.

Table 63: Multivariate Regressions Predicting Weight-Change between Leaving Slimming World and Follow-up

Variable	Coefficient	t-statistic
Age	-0.0774	-1.65
Start Weight	-0.0346	-1.25
Referral Member	-3.021	-1.76
Weight Change in the Slimming World Programme	-0.360**	-3.27
Time from the end of the Slimming World Programme to Follow-up	0.0916	0.31
Time from the end of the Slimming World Programme to Follow-up Squared	-0.00194	-0.29
Constant	5.280	1.18
N	226	

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

When including all variables, weight-change within the Slimming World programme was the only significant predictor, with each additional kilogram of weight-loss within the programme predicting 0.36kg more regain after leaving. The model found that each month after leaving the programme predicted an additional 0.09kg of weight-regain, with the rate of regain declining over time. As an example, the model was tested on a hypothetical individual with characteristics based on the mean of the 10,000 person sample of the Slimming World dataset, who attended the programme for 1-year and lost 3.44kg in the programme (the mean weight-loss predicted by the Heckman-correction model). The model predicted that for an individual that lost 3.44kg, the individual would have gained 0.78kg after 1-year outside of the programme and, and have regained a total of 1.04kg at 2-years.

8.4 Discussion

This chapter has provided answers to the two questions set out in the introduction by building regression models to predict a background weight-trajectory, and to predict weight-change after leaving a behavioural weight-management programme. The ELSA dataset provided information regarding long-term weight trajectories in the United Kingdom which can be used to predict long-term weight-change for participants of the Slimming World programme and the control group. The ELSA study provided a sufficient sample size from which to make reliable predictions, as well as being well balanced in terms of the characteristic of the individuals, including age, BMI, income and education. A key benefit of using this regression model to predict weight-trajectories is that the regression model was able to estimate the non-linear relationship with weight-change and age, and so took into account the different weight-change patterns at different ages.

The regression model estimating weight-change predicted that participants gain weight into their late 50s, which is likely caused by increasingly sedentary lifestyles as people age, combined with slowing metabolism (Luhrmann et al., 2009). As individuals age further, the loss in muscle-mass is greater than the decrease in metabolic rate and so individuals begin to lose weight over time, as shown in the weight-trajectory predicted by the regression model (English and Paddon-Jones, 2010). The regression model therefore makes predictions that reflect human biology and the effects of aging on weight, which can improve the accuracy of predictions about long-term weight-change in economic evaluations.

There were however limitations with the use of the ELSA dataset to predict long-term weight-change for the Slimming World population. The first limitation is that because the youngest individual in the dataset was 45 at the time of the first weight-measurement, any projections regarding weight-change before the age of 45 are outside the range of observed weight-change. The second limitation is that data from the ELSA dataset was recorded between 1998 and 2019, and so the assumption is made that future weight-change trajectories from 2019 onwards will mimic the patterns of weight-change seen over the last two decades. Finally, participants of Slimming World were all individuals who had signalled a desire to lose weight, whereas those in the ELSA dataset did not all necessarily have this desire. However, the data does still inform us of trajectories for individuals who did not receive any intervention and those who are no longer in, or receiving the effects of an intervention.

The regression model built in this Chapter using the ELSA data will be used to inform background weight-trajectories in the cost-effectiveness model. These trajectories will be used for the control group, and for the intervention group once the effect of the intervention is assumed to have dissipated. This has therefore provided a solution to the problem of unknown weight-trajectories for individuals in the long-term, and is an improvement on making a basic assumption of a flat rate of weight-change each year.

The analysis of this follow-up study completed by Slimming World has provided information regarding what happens to the weight of Slimming World attendees after they leave the programme, which is valuable for making predictions regarding weight-trajectories of Slimming World members when they leave the programme. The regression analysis found that whilst Slimming World members who stopped attending classes did not maintain as much weight-loss as those who were still attending classes at the time of follow-up, participants were still able to maintain some weight-loss. The change in bodyweight seen in the Slimming World follow-up study shows that both baseline- and last-observation carried forward analysis are flawed, as baseline-observation carried forward is overly conservative, whilst last-observation carried forward is overly optimistic.

One key finding is that despite those leaving the programme having a significantly lower amount of weight-loss at follow-up, over two-thirds of respondents had a lower body-weight than at baseline, and over half had maintained a clinically significant weight-loss of 3%. The regression analysis showed that individuals who lost more weight in the programme regained more weight at follow-up, but were still able to maintain more weight-loss than those who lost less weight.

A limitation exists in that the sample may be biased as it may be that those who responded to the survey would be more likely to have been successful at maintaining their weight-loss, with those who regained weight being less willing to report their weight-change. However, the upfront gift of a free pen, and the entrance into a raffle for prizes for completing the survey somewhat offsets this. As well as this, weights were self-reported, and so may suffer from bias (Robinson and Oldham, 2016). The meta-regression model predicting weight-change after BWM programmes, in Chapter 7, predicted that an individual with the same characteristics and weight-loss would have regained 1.53kg in the first year, and 3.07kg at year 2, which is a substantially greater weight-regain than predicted by the Slimming World regain model. This may be due to these biases, or it may be that Slimming World provides participants with a better ability to maintain weight-loss compared with other BWMs.

Another limitation is that this is a reasonably small sample size of 230 individuals in comparison to the total number of Slimming World members across the United Kingdom, and so generalisability to the full population may not be accurate. Also, the small sample size contributed to some explanatory variables not proving to be significant predictors of weight-change.

This regression model will be used to make predictions of weight-change for participants of behavioural weight-management programmes after leaving the programme. This is useful as it takes real-world observations of weight-change outside the programme and uses them to form projections for individuals whose long-term weight change is unknown. These weight-change projections will be used in cost-effectiveness modelling in order to gain an understanding of the impact on cost-effectiveness when assuming that Slimming World participants who leave the programme follow these predicted weight-trajectories.

Chapter 9: The Cost-Effectiveness Model for the Economic Evaluation of Behavioural Weight-Management Programmes

9.1 Background

The PhD has sought to explain the relationship between weight-loss in behavioural weight-management programmes and long-term weight following the programme. To improve estimations of the cost-effectiveness of weight-management programmes, projections of weight-trajectories should be established for the participants of the programmes. By doing this the effect of weight-management programmes on health outcomes and costs can be established over the course of a lifetime.

To establish these weight-trajectories, data was drawn from a number of sources:

1) Weight-change within the Slimming World programme was predicted using a regression modelling in Chapter 5 using Slimming World data and the theoretical framework of weight-management from Chapter 3, which was informed by the review of theories in Chapter 2.
2) Chapter 7 consisted of a systematic review and meta-regression of long-term follow-up of weight-management programmes with the aim of identifying patterns of weight-change after programmes ended.
3) A follow-up study, undertaken by Slimming World of their own members, was analysed in Chapter 8 to establish long-term weight-change after drop-out for Slimming World participants.
4) A longitudinal dataset of the effects of aging in the UK was analysed to create a background weight-trajectory for the population over time in Chapter 8.

Using these weight-trajectories, sophisticated predictions of the outcomes of weight-management programmes can be estimated. Finally, a systematic review of other economic evaluations of behavioural weight-management programmes was performed to identify assumptions made in other cost-effectiveness models, and to test these assumptions and compare the results with the results from the weight-trajectories predicted in this PhD.

To assess the potential impact of an intervention, cost-effectiveness analysis is required to estimate the change in health outcomes, as well as the change in costs, in order to provide better information to decision-makers (Williams et al., 2008). As the long-term effects to the participants, to the NHS, and to wider society are unknown, predictions must be made regarding disease incidence in the case of both whether the intervention is funded, and whether the intervention is not funded. Health outcomes and the associated costs can then be derived from the predictions of the effects of the intervention. Cost-effectiveness modelling can address this, with more sophisticated models providing more accurate estimates of cost-effectiveness of interventions.

In the case of weight-management programmes, the desired outcome is for participants to reduce their bodyweight. When evaluating a weight-management programme, the focus should therefore be the effects associated with change in bodyweight. Bodyweight, and disease incidence from bodyweight, should be compared in both the case of whether the intervention is applied, and whether the intervention is not applied. A cost-effectiveness model should then derive health outcomes and costs from the difference in bodyweight and predicted disease incidence in both the intervention and control group.

The key aim of this chapter is therefore to describe the decision model with a focus on the formation of sophisticated weight trajectory predictions for weight-management programme participants over the course of a lifetime by combining data from the preceding chapters. From here, the methodology behind estimating the benefits and costs for the case study, the Slimming World programme, the case, will be made. Finally, the process of the sensitivity analysis on input parameters and weight-trajectories will be explained.

9.2 Methods

9.2.1 The Cost-Effectiveness Model

To assess the cost-effectiveness of weight-management programmes, a Markov model was employed, which was taken from Meads et al. (2014). The model was then adapted in order to be more sophisticated and able to incorporate various weight-trajectory assumptions. A Markov model was chosen over a simulation model as a simulation model would have required a larger amount of data regarding the impacts of age, specific quality of life outcomes and interactions between disease states. The aim of the cost-effectiveness modelling was to assess the impact of adjusting weight-trajectories, which the Markov model was able to incorporate. Markov models were also recommended as appropriate to assess cost-effectiveness of weight-management programmes in Griffiths et al. (2012). Recreating a case-study of the Slimming World programme in Meads et al. (2014) was therefore chosen to be the most appropriate method.

The calculation of cost-effectiveness begins with the raw data of participants of the weight-management programme. According to this baseline data, weight-change each year is predicted by the various regression models and converted into an estimated BMI for each individual each year.

The second stage of the model takes these BMIs values, and categorises individuals into one of 5 groups: healthy weight (<25kg/m^2), overweight (25-29kg/m^2), obese (30-34kg/m^2), severely obese (35-39kg/m^2), and severely obese II (≥40kg/m^2). The model calculates the number of individuals in each group each year, and uses this information to create a transition percentage between BMI groups each year, and therefore dictate the number of people that move between each BMI group, each year.

After BMI groups each year are predicted, each individual can move between disease states according to the disease and mortality rates associated with the individual's age and BMI group. Participants continue to move between BMI groups and disease states for the duration of the model. Following this, the model trace shows the number of people in each BMI group, and each disease state each year, and assigns a QALY and cost value to each individual each year. These QALYs and costs are then compared between the intervention group and control group to permit an estimate of cost-effectiveness.

The following key updates were made to the cost-effectiveness model, and will be explained later in the chapter:

1) Individuals continue to be able to change BMI state even after moving into a disease state, so that BMI utility decrements and disease risk can still change according to BMI group.
2) Weight-trajectory projections were able to be implemented on an individual level, meaning that different projections by individual can be assessed, and different weight-trajectories can be applied to different individuals.
3) Weight-trajectory was able to be predicted through regression models inside the model, given the characteristics of individuals in the model.
4) An extension on the number of years modelled from 54 years to 57 years.
5) An extension to the number of individuals included in the modelled from 1,000 to 10,000.

9.2.2 The Case-Study of the Slimming World Cohort

For the Slimming World case study, a sample of 10,000 Slimming World members was selected from the 2014 dataset described in Chapter 4. This sample was randomly selected, using the sample command in STATA, although individuals had to have full data for four variables which were key to analysis. The first was height, which allowed calculation of BMI, target weight, as regression modelling used personal preferences regarding target weight as an explanatory variable, and both income and education IMD quintile, again as regression modelling used deprivation level as an explanatory variable. The reason for using a random sample was that as the full cohort is very large, it would have required a large amount of computing power. A random sample of 10,000 individuals was judged to be a large enough for the full cohort of Slimming World participants in 2014 would be accurately represented, and generalisations about the full cohort could be made. Participants were then simulated through the model from the age of 43, the mean age of the sample at baseline, until they reach the age of 100, as at this age an insignificant amount of the cohort were predicted to remain alive. The next section will discuss each stage of the cost-effectiveness model in more detail, and how the intervention cohort and control group progress through the model.

9.2.3 Weight-Change Trajectories in the Cost-Effectiveness Model

In the cost-effectiveness model, weight-trajectories for each individual were predicted. Rather than the weight-trajectories being predicted as a whole, the various stages of weight-change were grouped into three stages, and then combined to form an overall weight-trajectory. Three groups were created to define the various stages of the weight-trajectory formation, shown below:

1) Weight-loss in the weight-management programme
2) Weight-regain after leaving the weight-management programme
3) Background weight-trajectory

The first stage was the weight-loss phase, which in the case-study of Slimming World, lasted for two years, as the dataset used in the case-study contained up to two-years of data for each individual. An alternative scenario was also tested in which the weight-loss phase was assumed to be only 12-weeks, as GP referrals to Slimming World initially cover 12-weeks. The following stage was the weight-regain phase as Chapter 6 showed that often, participants of behavioural weight-management programme regain weight after leaving the programme. This weight-regain period lasted up to 6-years post-baseline depending on the scenario being considered, as after year 6, predicted weight-regain values tend to be similar to the background weight-trajectory. Following the weight-regain phase, participants proceeded to follow the background weight-trajectory, defined by population weight-trends. A diagram is shown in Figure 33, below.

Figure 33: The Three Stages of Weight-Change

For the intervention group, as 2 years of Slimming World data was available in the dataset provided, predicted weight-change from regression modelling was used to derive BMI values at years one and two. The meta-regression model predicting weight-change following weight-loss programmes was then used to predict weight-trajectories after the initial two years. After the effects of the intervention had ceased, the intervention group began to follow weight-trajectories at the background rate.

9.2.3.1 The Weight-Loss Phase

The first stage of building weight-trajectory predictions for the individuals in the cost-effectiveness model, was to make predictions of initial weight-loss during the intervention. For the Slimming World programme case study, these predictions were made when analysing the Slimming World dataset, in Chapter 5. Individuals in the intervention group were split into four groups according to when they left the programme: those who left before 3 months; those who continued attending past 3 months but left before 6 months; those that continued past 6 months but left before 12 months; and those that continued attending for over 1 year. These groups were labelled as the 3-month group, the 6-month group, the 12-month group and the 24-month group respectively. These groups were chosen to compare different patterns of attendance behaviour.

The 3-month group was to represent those individuals who dropped out before the initial 12-week programme had finished. The 6-month group represented those who completed the initial 12-weeks, but left the programme shortly after. The 12-month group consisted of those who continued to attend the Slimming World programme up to a year but not past the first year, whilst those in the 24-month group were those who either attended for over a year, including those that attended indefinitely.

A total of four different estimation methods for weight-change in the weight-loss period, at 12-months and 24-months, were implemented, and are listed below:

1) To apply Heckman-correction predictions of weight-change to all individuals at both 12-months and 24-months, as figures for body-weight were needed each year in the cost-effectiveness model.
2) To apply LOCF weight-change for all attendees at 12-months, and at 24-months for those in the 24-month group.
3) To apply BOCF weight to those in the 3-month and 6-month groups at 12-months, LOCF weight-change for those in the 12-month and 24-month group at 12-months and LOCF weight-change for those in the 24-month group at 24-months.
4) To apply complete-case analysis was performed by only considering LOCF weight-change in the 24-month group and BOCF weight for the other three groups.

In the base-case, scenario 1, the Heckman-correction predictions were used as the estimates of weight-change at year 1 and year 2, as these projections were assumed to be the most accurate projections of weight-change at the end of the initial 24-month weight-loss phase. In the second and third scenarios, those individuals to whom LOCF weight-change was applied at 12-months were assumed to have ended the weight-loss phase, and therefore move to the next weight-trajectory stage earlier than the 24-month group. This was as it was assumed that in these scenarios, after individuals leave the Slimming World programme, the weight-loss intervention was assumed to be over. For the complete-case analysis, the assumption was made that those in the 3-month, 6-month and 12-month groups did not change weight for the entire 24-month weight-loss period to focus the analysis on those in the 24-month group – the complete-case group.

9.2.3.2 Weight-Regain following the Weight-Management Programme

After the end of the initial weight-loss period, the cohort moved into the weight-regain phase. Two different weight-regain methods were considered. The first source of weight-regain information was from the meta-regression of long-term follow-up in weight-loss programmes. The second was the follow-up survey Slimming World carried out with participants that left the programme. A decision was made to limit the weight-regain phase to six years. This was for two reasons: the first was that on average after four years the weight-regain was smaller than the average background weight-trajectory, and so it was assumed the effect of the intervention had dissipated at this time point. The second was that only two interventions included in the meta-analysis of long-term weight-change included weight-change information over 6-years from baseline, and so there was a greater level of uncertainty for weight-change predictions past 6-years.

Another assumption made in the weight-regain phase, was that if the weight of a given participant rose above the trajectory in the control group, they joined the control group trajectory in the following period, and continued on the control trajectory for the remainder of the model's time-horizon. This assumption was made so that the model could not make a projection for an individual where attending the Slimming World programme led to the individual being at a higher weight long-term than if they had not attended.

Although there were only two sources of weight-regain information, there were many options of how these methods could be implemented following the weight-loss phase, and ways to apply the different regain types to the different groups of individuals. In the base case, the weight-loss phase was assumed to be the first 24-months for all participants, and so weight-regain from the meta-regression model was applied to predict weight-change after 24-months, and therefore BMI, up to 6-years.

9.2.3.3 Long-Term Background Weight-Trajectory

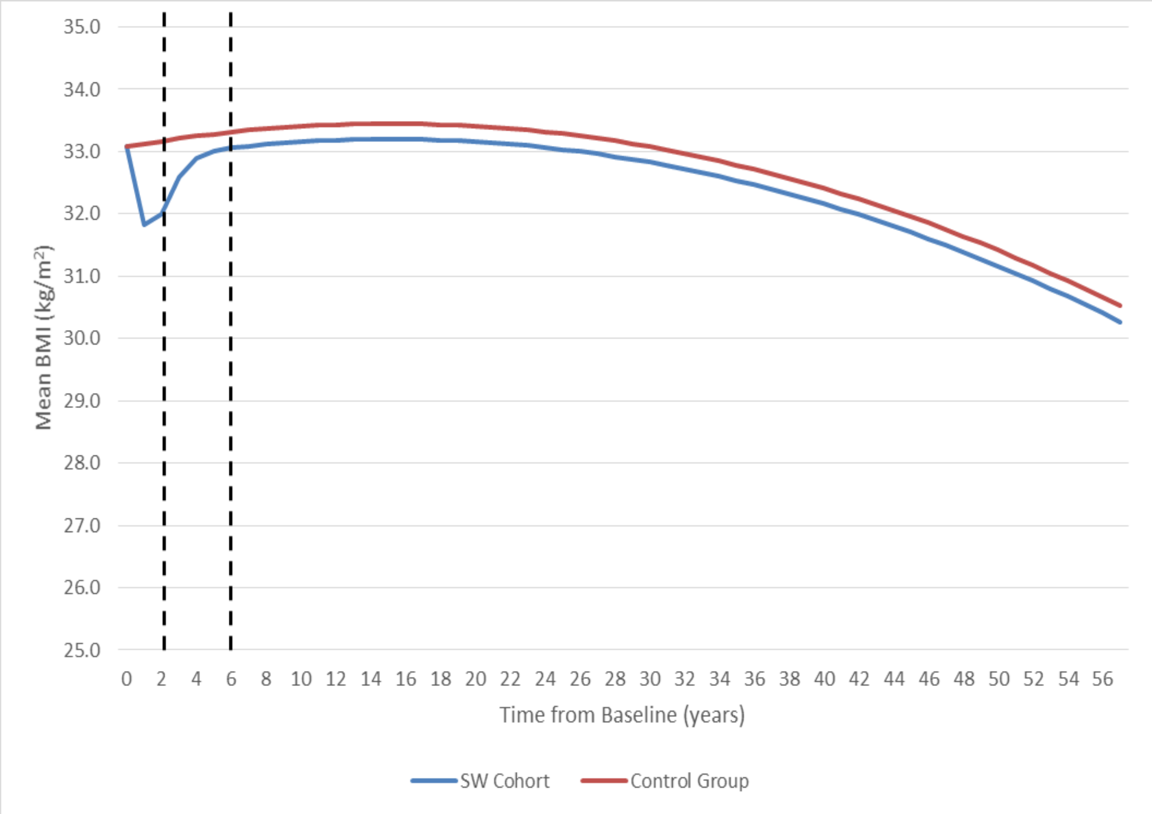
A background weight-change derived from the ELSA dataset was used in all scenarios as the most realistic assumption regarding long-term weight-change. This was as the trajectory was informed by real-world weight-change experienced in the general population, with weight-change being predicted by the regression modelling in Chapter 8.

After the effects of weight-regain following the weight-management programme were assumed to have stopped, and any remaining programme weight-loss was assumed to have been maintained, participants joined a background weight-trajectory predicted by a regression model informed by a panel dataset of UK society – The ELSA. In the base-case, the control group were assumed to follow the background weight-trajectory from baseline, as this weight trajectory indicates what would have happened to the cohort if they had not attended a weight-management programme. The background weight-trajectories were calculated for each individual by subtracting the predicted weight-change at baseline (where age was equal to baseline age) from the predicted weight-change at the given year.

9.2.3.4 Overall Trajectory of Weight-Change in the Base-Case

Following the predictions of weight-change, and therefore BMI, at each year for each individual in the model, weight-trajectories were created. Figure 34 shows a plot of mean BMI over time for both the intervention group and the control group in the base-case, with the dotted lines marking the end of the weight-loss phase and the end of the weight-regain phase. The plot shows that the Slimming World cohort lose weight in the first year before regaining some weight in the second year of the weight-loss phase on average. Following the weight-loss phase, weight is regained at a faster rate by the cohort, with the rate of weight-gain slowing over time. Participants then begin to lose weight again as the effects of aging appear. The control group gain weight initially before losing weight in the longer-term. Under the base-case assumptions, the Slimming World cohort maintain a lower mean BMI than the control group for the duration of the model.

Figure 34: Mean BMI over Time in the Base-Case

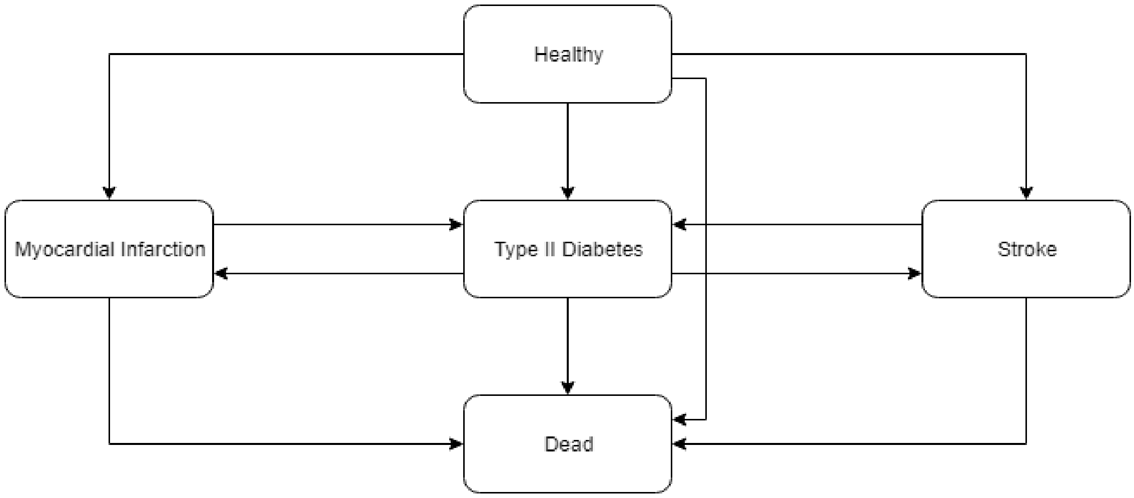


9.2.4 Health States and Mortality Rates

Whilst participants change weight according to their individual age, in the cost-effectiveness model, all individuals are assumed progress through the model at the same age, with this age having corresponding disease and mortality rates. In this case study the starting age is assumed to be 43 – the mean age of the Slimming World cohort at baseline. This was a simplifying assumption, but one which was hypothesised to have little significance as both the intervention and control group began at the same age. The simplification was made as simulating individuals through disease states based on various ages and BMI groups would make the model overly complex and require a large amount of computing power.

As well as facing a basic age-related mortality, participants are subject to disease risk according to their BMI group and the age of the cohort each year. Mortality and health state transition rates were assumed equal across genders. Three diseases were included in the cost-effectiveness model – T2D, MI and stroke, which were taken from the model in Meads et al. (2014). It is assumed that once an individual has either T2D, MI or stroke, they keep that disease for the remainder of the model period. Myocardial infarction and stroke were mutually exclusive, as once an individual in the model transitions to one of the two disease states, they cannot contract the other. However, these individuals can become diabetic, and those with T2D can experience a stroke or MI. Individuals who experience MI or stroke cannot remain in the year 1 state, and instead either move into the year 2 state, or a different MI or stroke health state. This is because if an individual initially survives MI or stroke, the following year is assumed to bear a lower risk of death, a greater quality of life, and lower cost than first year of the health event. Individuals that experience MI or stroke are also able to experience a second MI or stroke in the model. A simplified illustration of the model, which depicts only the three diseases is shown in Figure 35, below.

Figure 35: Health States in the Cost-Effectiveness Model



Whilst there were only three diseases included in the model, various stages and combinations of diseases resulted in a total of 15 health states, including healthy and death, shown in Table 64. The table shows an example of transition rates from healthy for an individual aged 43 in the severely obese II group. The table shows there is a 94.9% chance that the individual remains healthy in the next period, with varying degrees of probability of moving into a disease state, and a 0.2% probability of death.

Table 64: Health States and the Transition Rates from Healthy at Age 43 for Severely Obese II Group

Age 44 Health State	Probability of Transition from Healthy
Healthy	0.949
Diabetes	0.0283
MI Year 1	0.0160
MI Year 2	0
Stroke Year 1	0.00291
Stroke Year 2	0
MI x 2 Year 1	0.000650
MI x 2 Year 2	0
Stroke x 2 Year 1	0.000323
Stroke x 2 Year 2	0
Diabetes + MI Year 1	0.000452
Diabetes + MI Year 2	0
Diabetes + Stroke Year 1	0.0000822
Diabetes + Stroke Year 2	0
Dead	0.00153

See Meads et al. (2014) for references

In the model, all 10,000 individuals began in the ‘healthy state’, in which participants received no negative impact on quality of life from disease. This assumption was made as weight-management programmes are viewed as preventative care, and are therefore designed to target weight-loss in individuals that are high-risk, but without disease. As well this this, the assumption is offset by the control group having identical baseline characteristics as the intervention group as the differences in QALYs gained and costs are still comparable. Therefore, in the model the assumption is that the intervention is applied to 10,000 high-risk, but otherwise healthy individuals.

Each year, participants then move through BMI groups and disease states based on their current BMI group, current disease state and age. Figure 36 shows how many individuals in the Slimming World cohort were in each BMI group each year when including mortality. It can be seen that the number of people in each group declines over time, with the number of people in the larger BMI groups declining at a faster rate, due to the increased rate of mortality within these groups.

Figure 36: BMI Groups over Time (with mortality)

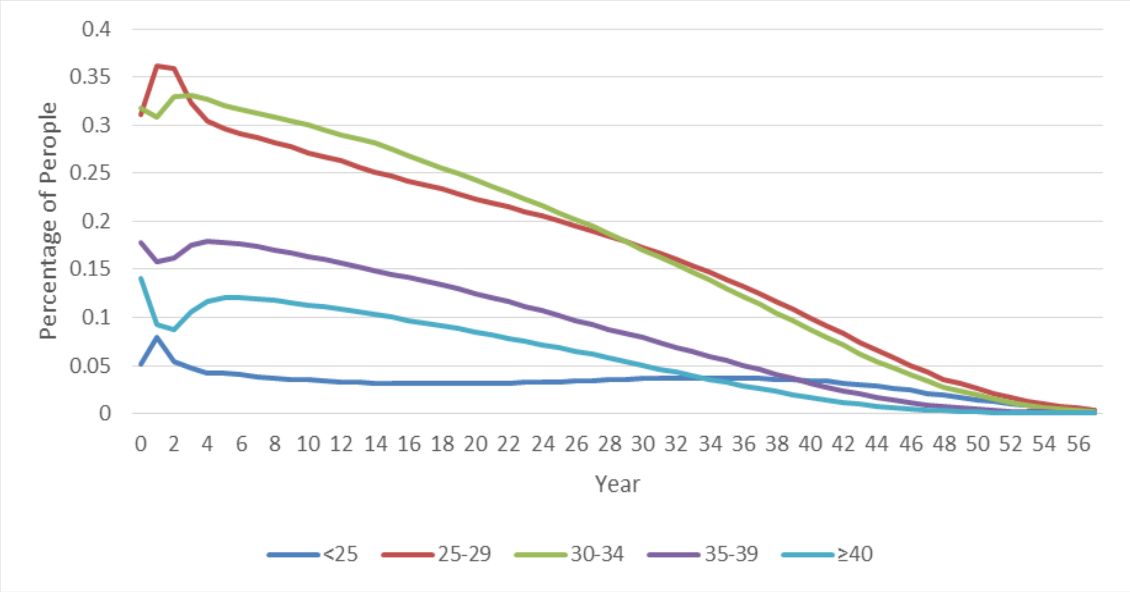


Figure 37 shows this trend more clearly, with the proportion of individuals with obesity at baseline being the same, and the proportion of those with obesity reducing due to higher rates of mortality. At year 57, it can be seen that without mortality, over 20% of the cohort would be in obese, severely obese or severely obese II group, whilst with mortality, only around 7% of the cohort are in these groups.

Figure 37: Proportion of Cohort with Obesity over Time

9.2.5 Model Output Validation

When reviewing the plausibility of weight-trajectory outputs, BMI trends, and mortality, were compared against real-world data. The first stage was to compare the mean BMI of the model cohort at age 80 with the mean BMI of the average Slimming World participant in the full dataset at age 80. The mean BMI at year 37 (when the cohort was 80 on average) was 32.40kg/m^2 in the intervention group, and 32.60kg/m^2 in the control group, compared with a mean BMI of 32.25kg/m^2 for 80 year olds that are in the Slimming World dataset.

When reviewing life expectancy of the cohort, individuals had a life expectancy of 72.84 years in the intervention group in the base-case, and 72.79 years in the control group. This estimation was lower than the average life expectancy in the UK, but this is explained by two factors (Office for National Statistics, 2018). The first is that as the sample of individuals has a greater obesity prevalence rate throughout the lifetime of the cohort, the mortality risk each year is greater, which leads to a lower life expectancy. The second reason is that because the age-related mortality rates used in the decision model included mortality from type II diabetes, myocardial infarction and stroke, mortality from these diseases were counted twice, which led to inflated mortality rates.

9.2.6 Health Utility States and Healthcare Costs

Following the calculation of the number of individuals in each BMI and health state each year, health outcomes and costs were calculated. Each age was associated with a utility value, taken from the model in Meads et al. (2014). These values are shown in Table 65, with younger individuals generally having higher health-related quality of life.

Table 65: Base Utility for Each Age Group

Age Group	Base Utility
16-24	0.938
25-34	0.918
35-44	0.897
45-54	0.856
55-64	0.818
65-74	0.779
75+	0.715

After QALY values have been calculated for each individual each year, deductions from that QALY value are made according the BMI group each individual is in each year (Table 66), and the disease state each individual is in each year (

Table 67). Utility decrements from BMI and disease state were additive. Disease states were assumed to be mutually exclusive, other than type II diabetes, which could be combined with any other disease state. Where individuals were both type II diabetic and in another health state, utility decrements were additive. It was assumed that those who died received 0 QALYs per year. Following this process, total QALYs were calculated by taking the sum of the cohorts QALY values each year, and applying a discount rate of 3.5% per year. A discount rate of 3.5% was chosen as this was the discount rate used in the original model in Meads et al. (2014), and the discount rate most commonly employed in the decision models in the literature from the systematic review of economic evaluations in Chapter 6.

Table 66: Utility Decrements by BMI Group

BMI Group	Utility Decrement
BMI <25	0.000
BMI 25-30	0.006
BMI 30-35	0.033
BMI 35-40	0.033
BMI >40	0.117

Table 67: Utility Decrements by Disease State

Disease State	Utility Decrement
Type II Diabetes	0.096

Stroke Year 1	0.160
Stroke Year 2+	0.080
MI Year 1	0.139
MI Year 2	0.070

A similar method was applied when calculating costs. In the base-case, the cost of the intervention was assumed to be £121.32 per person. This figure considered the total cost from the perspective of a service provider, and so represented three separate costs. A cost of £47.39 for each individual for the first 12-weeks, which was used by the model in Meads et al. (2014), a set-up cost of £22 per person, which were both covered by the GP. In addition to this, it was assumed that all additional attendances made by participants following the initial 12-weeks came at a cost of £4.95. The average participant attended an additional 10.5 classes, and so each participant was assumed to pay an additional £52.05 on average. Each health state was then assumed to carry a cost, shown in Table 68. Both healthy and death were assumed to cost zero, whilst costs for dual disease states were assumed to be additive. Total costs were calculated by taking the sum of the cohort's costs each year, and again applying a discount rate of 3.5% each year.

Table 68: Cost of each Health State each Year

Disease State	Cost
Type II Diabetes	£2,765.17
Stroke Year 1	£11,968.89
Stroke Year 2	£1,642.77
MI Year 1	£5,895.42
MI Year 2	£260.82

Following the calculation of costs and QALYs for the intervention cohort, the same calculation was performed on the control group to identify the total QALYs and costs that would have been obtained from the cohort had they not been provided with an intervention. Cost-effectiveness was then calculated via an ICER, with the formula shown in Equation 37.

Equation 37

$$ICER = \frac{Intervention\ Cohort\ Cost - \text{Control Group Cost}}{\text{Intervention Cohort QALYs} - \text{Control Group QALYs}}$$

The equation calculates the incremental cost of providing the intervention, over the incremental benefit received by providing the intervention, to produce a figure for the cost of one quality-adjusted life year gained. Calculations of net benefit were made using a cost-effectiveness threshold of £20,000 per QALY as a conservative estimate of the £20,000 to £30,000 per QALY threshold that is used by NICE in the UK (Paulden, 2017). The formula is shown in Equation 38.

Equation 38

$$\text{Net Benefit} = \text{Incremental QALYs} * \text{Cost} - \text{Effectiveneess Threshold}) - \text{Incremental Cost}$$

Comparisons were then made between outcomes in the intervention group and control group. The incremental differences between the outcomes of the two-groups were tested using one-tailed z-tests. One-tail was used as the null hypothesis was that the intervention group outcomes were not significantly better than the control group outcomes, with the alternative hypothesis being that the intervention outcomes were an improvement over the control group.

9.3 Sensitivity Analysis of the Base Case

Sensitivity analysis is necessary to analyse the impact of changing model parameters and assumptions on estimates of cost-effectiveness (Briggs et al., 2012). This is because of underlying uncertainty around values used in the models and the assumptions made, which lead to uncertainty in estimates produced. Two types of sensitivity analyses were performed in the cost-effectiveness model – sensitivity analyses to assess parameter uncertainty, and scenario analyses to assess structural uncertainty.

The first stage of assessing the impact of parameter uncertainty was to perform one-way sensitivity analysis, by adjusting each parameter between 75% and 125%, in order to test the robustness of the model, and how influential each parameter input was to overall estimates of cost-effectiveness. Sensitivity analysis was first conducted around groups of conducted around the following parameters:

- Utility decrements of each health state and BMI group

- Health state costs
- Mortality rates
- Disease transition probabilities
- Discount rate
- The cost of the intervention

As well as adjusting the discount rate in one-way sensitivity analysis, an alternative discount rate of 1.5% was also tested. This was because NICE guidelines suggest that public health interventions should also consider a discount rate of 1.5% for costs and health effects (NICE, 2018).

As predictions of weight-change are unobserved, and therefore estimates, sensitivity analysis was also carried out on the estimations. Sensitivity analysis was undertaken by creating prediction intervals around each point estimate, rather than making the assumption that each point estimate is a fixed value (Briggs et al., 2006). The regression models predicting BMI change at each year were made probabilistic using guidance from Briggs et al. (2006). PSA was applied to the regression BMI predictions each year via the Cholesky decomposition, which was needed to control for correlated parameters in regression modelling. This created a distribution of values for each coefficient in each regression model, with a random draw taken from this distribution, and used in the regression model in each probabilistic model simulation. For the remainder of the parameters PSA was applied to, probability distributions were used around point estimates with random draws taken from the distributions each simulation.

The PSA was performed by taking random draws from each probability distribution each year, and running the model simulation with each set of random draws to determine values for outcomes in both the intervention and control group. Estimates of cost-effectiveness were then taken from these outputs. A total of 10,000 Monte Carlo simulations were performed, allowing generation of an ICER from the means and net benefit estimate. The incremental QALYs and costs estimated in each Monte Carlo simulation were then plotted on a cost-effectiveness plane (Cohen & Reynolds, 2008). The latter was used to estimate the likelihood that the intervention was cost-effective across a range of willingness to pay per QALY gained thresholds which were plotted on the cost-effectiveness acceptability curve (Fenwick et al., 2004).

9.4 Alternative Scenario Analysis

Following sensitivity analysis of the uncertain parameters in the cost-effectiveness model, the next phase was to assess the structural uncertainty regarding the assumptions made about weight-trajectories. These scenarios were tested to identify the impact of adjustments to weight-trajectories, and the influence these assumptions have on predictions of cost-effectiveness, which would illustrate the importance of improving the accuracy of weight-trajectory predictions. The scenarios tested are shown in Table 69, below, with the assumptions regarding the weight-loss phase and weight-regain phase for the intervention group stated for each. After the weight-loss phase, individuals move into the weight-regain phase, and when that is complete, individuals follow the background weight-trajectory.

The scenarios were taken from the potential applications of the various data regarding weight-trajectories, discussed in the weight-trajectory section earlier in this chapter. These weight-change trajectories were chosen to illustrate the range of possibilities for long-term weight-change.

Table 69: Weight-Loss and Weight-Regain Scenarios

Scenario	Weight-Loss	Weight-Regain
1 (base case)	Heckman weight-loss projections for all groups at years 1 and 2	Weight-regain from meta-regression for all groups from up to year 6
2	Heckman weight-loss projections for all group at year 1 Heckman weight-loss projections for only the 24-month group at 2 years	Regain to year 3 from the Slimming World follow-up study for those in the 3-month, 6-month and 12-month groups Weight-regain from the meta-regression for those in the 24-month group up to year 6
3	LOCF weight-change for all groups at years 1 and 2 years	Weight-regain from meta-regression for all groups to year 6
4	LOCF for all groups at year 1 LOCF for the 24-month group at year 2	Regain to year 3 from the Slimming World follow-up study for those in the 3-month, 6-month and 12-month groups Weight-regain from the meta-regression for those in the 24-month group up to year 6
5	BOCF for those in the 3-month and 6-month groups at year 1 LOCF weight-change at year 1 for those in the 12-month and 24-month groups LOCF weight-change at year 2 for the 24-month group	Weight-regain from meta-regression for those in the 24-month group

*Individuals who reach the control group weight-trajectory during weight-regain continue on the control trajectory

9.5 Alternative Scenarios taken from the Literature of Economic Evaluations

As well as considering the 5 alternative scenarios of weight-change in Table 69, assumptions made in the literature were also tested in the model. These alternative scenarios, including the scenario in the Meads et al. (2014) paper, were identified in the systematic review of modelling methods for weight-management programmes, in Chapter 6. These assumptions regarding weight-trajectories from the literature were tested in the model to assess the impact of these assumptions on the patterns of weight-change over time, and the costs and effects derived from these patterns. These scenarios are listed in Table 70, below, and were compared against the control group in the base-case. Where multiple values of regain and regain time frame were mentioned, median, minimum and maximum values were tested, which were used in a tornado plot. Where background rates were employed in the literature, the background rate used in the base-case was used. This was because the background rates were used in both intervention groups and control groups, and using two different background rates would not be representative of the assumptions used.

Table 70: Alternative Weight-Change Scenarios in the Intervention Group

Scenario	Intervention Group Assumption	Values of Regain Used	Reference
6	No regain after weight-loss	N/A	Gray et al. (2018), Zomer et al. (2017), Smith et al. (2016), Wilson et al. (2015), Gustafson et al. (2009), Bemelmans et al (2008), Olsen et al. (2005), Meads et al. (2014), Miners et al. (2012)
7	Decay of effect each year	0%, 50%, 100%	Ginsberg et al. (2012), Cobiac et al. (2010)
8	Regain BMI points each year until background rate met	0.18, 0.36 and 1.87 BMI per year until background rate met	Lewis et al. (2014), Forster et al. (2011)
9	Linear regain over time to match control trajectory	Control trajectory met at years 3, 5, and 12	Thomas et al. (2017), Haussler and Breyer (2016)
10	Regain BMI points each year until baseline	0.15 BMI points per year, 0.3 BMI points per year, 1.08 BMI points in the first year then 0.36 BMI points per year	Hoerger et al. (2015), Fuller et al. (2014)
11	Linear regain to baseline	Baseline met at year 3 and year 4, and met after maintaining for 6 years then regain to baseline over next 4 years	Ahern et al. (2017), Trueman et al. (2010), Galani et al. (2007)
12	Probability of full weight-regain	67% probability of regain at year 3, 20% probability of maintenance at year 7	Michaud et al. (2017), Roux et al. (2006)

9.6 Scenario analysis on the Control Group and Background Trajectories

For the control group, multiple scenarios of weight-change were tested. These consistent of hypothetical weight-loss, if ‘usual care’ was considered successful for the control group, and various methods of implementing the background weight-trajectory. The first scenario was assuming that in the initial 2-year weight-loss phase, the control group maintained their baseline weight, and joined the background weight-trajectory at 2-years (control group scenario 2). This was a conservative assumption, as one would expect those who did not get referred to Slimming World to follow the background weight-trajectory. However, as the control group may have been provided the usual care, which was assumed to be GP information about weight-loss, some of these may have been able to lose weight. Another scenario was considered where in the first year, the control group lost 1kg, and maintained this weight-loss at 2-years, before joining the background weight trajectory (control group scenario 3). The final scenario considered was assuming that participants maintained their baseline weight up to year 6 – which was the end of the weight-regain phase in the base-case, and when all intervention group participants joined the background weight-trajectory (control group scenario 4).

9.6.1 Analysis of Background Weight-Trajectories

To test the effects of background weight-trajectories, alternative trajectories were applied to control group scenario 4, where all participants joined the background weight-trajectory at year 6. The effects of applying no weight-change (background scenario 2), as well as a 1kg per year weight-gain (background scenario 3), on incremental costs and effects after 6-years were tested as extreme values of weight-change as well as 0.429kg per year (background scenario 4), which Meads et al. (2014) employed in their decision model (Miners et al., 2012; Trueman et al., 2010).

9.7 Alternative Programme Consideration

As well as considering various assumptions regarding weight-change and weight-regain, an alternative scenario was considered in which only weight-change within the initial 12-week programme was considered. Weight-change at 1-4 years was predicted by the meta-regression model of weight-regain using LOCF weight-change within the first 12-weeks. This scenario was analysed to understand the potential outcomes if only the initial 12-week period that GPs can refer participants to the Slimming World programme for was focussed on, and it was assumed that after this period of referral, the intervention ended.

9.8 Probabilistic Sensitivity Analysis of Selected Scenarios of Weight-Change

To assess the overall potential impact of weight-trajectory assumptions, best-case and worst-case scenarios were assessed against the base-case, at both 6-years and over a full lifetime horizon. The scenario in Meads et al. (2014) was selected as the cost-effectiveness model was taken from Meads et al. (2014). The scenarios are shown in Table 71, below, with each assumption in the scenarios taken separately from the chapter and combined into a new scenario of overall weight-trajectory. A total of 1,000 Monte Carlo simulations were run for each scenario for the 2-year, 6-year, and lifetime time horizons. The number of simulations was chosen as 1,000 simulations was judged to be a large enough number of simulations to draw meaningful conclusions, without taking a long time to run.

Table 71: Selected Scenarios for PSA

Scenario	Weight-Loss	Weight-Regain	Background Rate
Best-Case	Scenario 3	Scenario 6	Background Scenario 2
Worst-Case	Scenario 5	Scenario 8 with control group matched at year-3	Background Scenario 3
Meads et al. (2014)	Base-Case	Scenario 6	Background Scenario 4

The base-case and best-case scenarios were then extrapolated to the full adults population of the United Kingdom to gain an idea of the potential difference in effect if all individuals that were overweight or obese participated in the intervention. This extrapolation was performed by first taking an estimate of the full population of the UK from the Office of National Statistics (2019) of 66,435,600. This figure was then multiplied by the estimated proportion of individuals that are overweight or obese in England and Wales from the NHS (NHS Digital, 2019), of 64%. This produced an estimated total population of 42,518,714 adults. The values for incremental QALYs and costs were then multiplied by this figure and used to calculate cost-effectiveness.

9.9 Hypothetical Scenarios of Weight-Change and Weight-Regain

The final analysis was to assess cost-effectiveness outcomes for different combinations of initial weight-loss and different periods of time in which weight-loss is regained. Ten separate values for weight-change were used (0.5kg-5kg) and compared against ten separate values for time period of weight-regain (1-year to 10-years). Participants regained weight to match the control group, who followed the background weight-trajectory from baseline. The ICER for each combination of weight-change and weight-regain assumption was noted in a two-way sensitivity analysis table, with non-cost-effective, cost-effective, and cost-saving combinations being highlighted. The purpose of this analysis was to identify the effect of small changes to both weight-change assumptions and weight-regain assumptions on cost-effectiveness, and at what level of weight-change and weight-regain does the intervention become cost-effective, or cost-saving.

9.10 Discussion

This chapter has introduced the decision-analytic model that is able to incorporate various assumptions regarding weight-loss and long-term weight-trajectories of individuals over the course of a lifetime. The chapter has also helped to explain how weight-trajectories are input into the model, how participants move through BMI groups and health states within the model, and how cost-effectiveness is calculated. The chapter has also set out the analysis of the Slimming World case study, and the scenarios and different assumptions that will be applied to the case study, in order to assess the impact on outcomes of adjusting long-term predictions of weight-trajectories.

The strengths of this model are that various weight-trajectory patterns can be incorporated into the model, and that sophisticated weight-trajectories can be predicted within the model using basic information routinely collected in weight-management programmes. Another strength is that individuals in the model can change BMI state whilst being in a disease state, and disease risk changes accordingly. The comprehensive probabilistic sensitivity analysis, and scenario analysis has allowed the testing of the impact of changing scenarios. This has informed us of the various potential outcomes that could occur due to the intervention, and the impact of choices made by other modellers in their analyses.

A Markov model was chosen as it was judged to be able to fulfil the aim of illustrating the impact of changing assumptions of weight-trajectories, whilst also remaining simplistic enough to not require large amounts of data, computational power, and time. The majority of models in the review of economic evaluations in Chapter 6 also employed Markov models, and so using a Markov model allowed comparison.

However, there were limitations to using a Markov model. The Markov model employed used a limited range of disease states, whilst a simulation model would have been able to more easily accommodate more complex disease states. Not including the possibility of individuals having both MI and stroke was made for simplicity, but this is a limitation as individuals can have both diseases and they may interact (Putaala and Nieminen, 2018). By making the two diseases mutually exclusive, the cost-effectiveness model likely underestimates the benefits of the intervention. This is because an individual experience both MI and stroke would have a further deduction to their quality of life, and an increase to the cost of treatment for the individual. Because the likelihood of having both diseases would be lower for those not in the intervention group, due to lower disease risk due to weight-loss, the benefits of the intervention would be greater.

Stroke, MI and T2D were the diseases chosen to be included in the model because T2D and CVD were the most common co-morbidities modelled in the past evaluations in Chapter 6. Forms of cancer were considered for inclusion within the model but were not used. This was because only 7 of 22 past decision models and 3 of 12 Markov models in the review of economic evaluations in Chapter 6 included cancers, and inclusion would have made the model much more complex. It was therefore decided that the aims of the study could be achieved without incorporating cancers in the decision model.

If a larger range of diseases associated with obesity, such as cancers, were included, the cost-effectiveness for the intervention estimated would likely be increased. As a higher BMI would cause higher rates of obesity-related diseases, and the intervention group has a lower BMI than the control group, the intervention group would have lower rates of disease, and therefore lower disease incidence. Because of this, the QALYs gained in the intervention group over the control group would increase and the benefits of the intervention would increase. Therefore, the model likely underestimates cost-effectiveness.

Because of this, the health benefits that are shown in the model underestimate the health benefits in the real-world. Therefore, by not including every disease and disease state, the cost-effectiveness of the intervention is underestimated. In addition to the increased health benefits estimated by the model by including more disease states, the difference in costs between the intervention and control groups would also be increased. This is because individuals in worse health would incur a greater cost as they require treatment. This would enhance cost-effectiveness further.

A discrete patient simulation model may have provided more accurate information regarding cost-effectiveness of interventions as individual patient histories would have been able to be incorporated within the model, and heterogeneity could be captured (Standfield et al., 2014). However, a more complex decision would have required a different approach in terms of both model type and software, and because of patient histories and patient-level data, would have required a larger amount of computing power, especially when performing comprehensive sensitivity analysis (Briggs et al., 2006). Patient-level data would have also been difficult, or even impossible to identify. For example, utility values in a given year would not only rely on current age, BMI and current health state, but on past health risks and disease incidences, and would have to be patient level. Being able to find the appropriate data inputs would be challenging.

Markov models were also the most commonly used models in the review of decision models in Chapter 6. The aim of the cost-effectiveness modelling was to assess the impact of adjusting weight-trajectories, and recreating a case-study of the Slimming World programme in Meads et al. (2014) was the chosen to be the most appropriate method. However, it should be noted that by underestimating cost-effectiveness in the decision model, the effect of changing weight-trajectories is also likely to be underestimated, as each additional kilogram of weight-loss provides less benefit in the model than in the real-world.

A key limitations is that for the weight-trajectories, as the predictions of weight-change are based on averages, there is a lower variance in weight-change than may be present in the real-world. In reality, there may be some individuals that gain more weight than they lost during the Slimming World programme, and some individuals that continue to lose weight after leaving the Slimming World programme. However, regression models will use the data available to make a projection of weight-change for each individual, and these projections will tend to the average expected value of weight-change.

As well as this, there were no gender differences according to disease rates and mortality within the model. Costs and QALY discounts for diseases were also assumed to be additive, which was a simplifying assumption, and Mortality rates associated with MI and stroke did not change over time.

Another limitation was that only three disease states were included in the model. As only type II diabetes, stroke and myocardial infarction were the only diseases related to obesity included in the cost-effectiveness model, the cost-effectiveness of interventions may be understated by estimations made by the model. It is possible that the weight-reduction seen in the intervention group may have contributed positively through increase in quality of life unobserved by the model.

As well as cost-effectiveness potentially being underestimated due to not all disease states being included in the model, there are potential spill over effects that have been found when individuals attending weight-management programmes. These spill over effects come from when individuals who attend these programmes are in families and encourage their partners and children to improve their lifestyles through improving diet quality and frequency of exercise. This creates positive effects on public health which is again unobserved by the cost-effectiveness model.

The next chapter will use the cost-effectiveness model described in this chapter to make estimations of the cost-effectiveness of the Slimming World. Following this, sensitivity and scenario analysis will be performed to assess the impact of changing assumptions, and identify the importance of using sophisticated methods of projecting long-term weight-change.

Chapter 10: The Results of Cost-Effectiveness Modelling and the Impact of Changing Assumptions of Effectiveness

This chapter will present the results of cost-effectiveness modelling, with reference to the final aim of the PhD – to investigate the impact of changing assumptions on estimates of cost-effectiveness. The stages of analysis performed in this chapter were set out in the previous chapter, which discussed the methods of cost-effectiveness modelling. This chapter first assesses the base-case scenario of weight-trajectories with deterministic parameters. Following this, sensitivity analysis of the base-case was performed to identify the influence of parameters and the ranges of estimates to cost-effectiveness estimates through varying these parameters. Following this, various scenarios of weight-change trajectories in both the intervention group and control group were analysed.

10.1 Results from the Base-Case Scenario

The first stage of analysis using the cost-effectiveness model was a deterministic analysis of the base-case using point estimates of parameter values, with the assumptions in the base-case being derived through the theoretical and empirical findings throughout this PhD. The base-case weight change assumptions were run in the model initially to assess the effects of the intervention against the control group under the base-case assumption – where individuals follow the background weight-trajectory from baseline for the full duration of the time horizon.

Table 72 shows the outputs of the model against the control group in terms of the BMI of participants, the disease rates, and the mortality rate at two time points, 2-years and 6-years. Two-years represented the end of the maximum potential time an individual could be involved in the Slimming World programme in the model, and 6-years was the point at which all weight had been regained and all participants had re-joined the background weight-trajectory. Mean BMI was shown for the full 10,000 sample of participants. Outputs at the end of the time-horizon were not shown as at the end of the time-horizon, 99% of both the intervention and control groups had reached mortality.

Table 72: Outputs from the Base-Case at 2-Years and 6-Years

Measure	Slimming World	Control Group	Incremental Value
2-Year Outcomes			
Mean BMI without mortality (kg/m^2)	32.00	33.17	-1.17
BMI >30kg/m^2 (%)	58.3	63.2	-4.9
BMI >40kg/m^2 (%)	8.8	14.2	-5.4
6-Year Outcomes			
Mean BMI without mortality (kg/m^2)	33.07	33.32	-0.25
BMI >30kg/m^2 (%)	65.2	65.6	-0.4
BMI >40kg/m^2 (%)	13.0	14.5	-1.5

Table 72 shows that Slimming World was effective at reducing the proportion of individuals with BMIs over 30kg/m^2 and 40kg/m^2 at the end of the intervention period, as well as at 6-years, although the incremental value was lower at 6-years.

Table 73 shows the outcomes across the different time horizons in terms of life years. The table shows Slimming World provided a marginal amount of life years at 2-years and 6-years, but provided a larger amount of healthy life years and QALYs. This was likely because all participants enter the model at age 43, and mortality around this age caused by a high BMI is unlikely. Over the full lifetime time-horizon, the Slimming World programme provided an additional 0.059 life years per person and 0.147 life years in the healthy state. When adjusting life years for quality of life, Slimming World provided an additional 0.056 QALYs per person over the full time-horizon.

Table 73: Health Outcomes in the Base-Case

Measure	Slimming World	Control Group	Incremental Value
2-Years			
Life Years	1.989 (1.988-1.991)	1.989 (1.988-1.991)	0.000 (0.000-0.000)
Healthy Life Years	1.928 (1.919-1.937)	1.922 (1.912-1.932)	0.006 (0.004-0.008)
QALYs	1.689 (1.673-1.705)	1.676 (1.659-1.693)	0.013 (0.010-0.016)
6-Years			
Life Years	5.843 (5.818-5.868)	5.842 (5.817-5.867)	0.001 (0.000-0.003)
Healthy Life Years	5.483 (5.426-5.549)	5.468 (5.411-5.534)	0.015 (0.004-0.033)
QALYs	4.468 (4.412-4.526)	4.446 (4.389-4.506)	0.022 (0.012-0.035)
Lifetime			
Life Years	28.846 (27.700-29.979)	28.787 (27.650-29.897)	0.059 (0.001-0.206)
Healthy Life Years	24.452 (23.137-25.790)	24.305 (23.013-25.600)	0.147 (0.015-0.458)
QALYs	13.433 (12.958-13.924)	13.377 (12.895-13.865)	0.056 (0.016-0.144)

*95% confidence intervals in parentheses

The costs derived for each group in the base-case scenario in the model are shown in Table 74, below. The table shows that at 2-years, the intervention costs an additional £100.63 per person on average, with the incremental cost being reduced when considering a longer time-horizon of 6 years. When considering a full lifetime time-horizon, the intervention is cost-saving due to the lower disease rates reducing the burden of care on health-care providers in the long-term. This is important when considering the current financial climate and the scarcity of resources available to health care commissioners.

Table 74: Costs in the Base-Case

Measure	Slimming World	Control Group	Incremental Value
2-Year Costs	£425.12 (£291.50-£602.21)	£324.49 (£182.43-£508.64)	£100.63 (£85.18-£113.71)
6-Year Costs	£1,301.94 (£805.95-£1,907.10)	£1,224.16 (£708.10-£1,850.44)	£77.78 (£23.69-£110.67)
Lifetime Costs	£7,096.61 (£3,956.99-£11,042.31)	£7,133.09 (£3,916.47-£11,230.23)	-£36.47 (-£354.95-£100.25)

*95% confidence intervals in parentheses

Table 75 shows the estimates of cost-effectiveness, derived from the QALYs and costs presented in Table 73 and Table 74 respectively. The table illustrates that the intervention is cost-effective under all three time-horizons under a cost-effectiveness threshold of £20,000 per QALY. When considering longer time-frames, the intervention becomes more cost-effective as the effects of the intervention have more time to manifest themselves. Over the course of a lifetime, the intervention dominates the control group, with a net benefit of £1,157.99 per person. This is a large return when considering the cost of funding the intervention was only £121.32 per person.

Table 75: Cost-Effectiveness Outcomes in the Base-Case

Measure	Incremental Value
2-Years	
Cost per QALY	£7,584.04 (£5,981.39-£10,783.58)
Net Benefit	£164.74 (£90.61-£218.60)

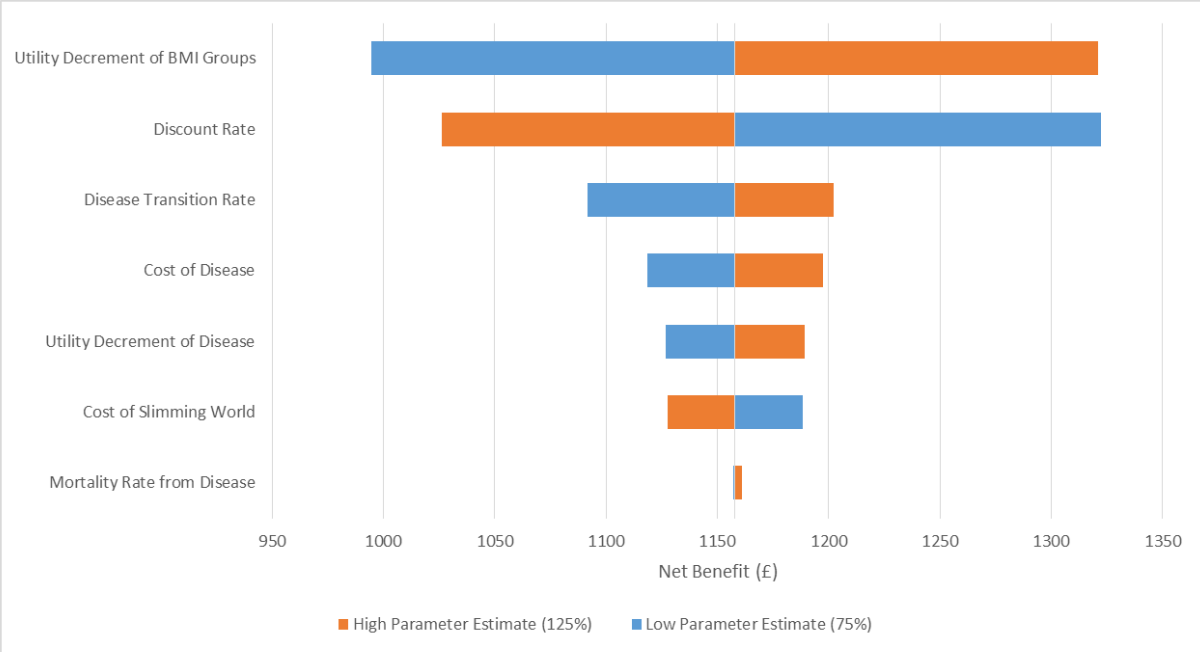
6-Years	
Cost per QALY	£3,536.14 (£767.94-£8,93.82)
Net Benefit	£362.15 (129.95-£658.63)
Lifetime	
Cost per QALY	SW dominates (-£3,595.80-£5,950.67)
Net Benefit	£1,157.99 (£223.04-£3,195.08)

*95% confidence intervals in parentheses

10.1.1 One-Way Sensitivity Analysis

To assess the robustness of estimations of cost-effectiveness made by the model, the impact of each parameter group within the model was tested. By setting each group of parameters to 75% and 125% of the deterministic point estimate in turn, the tornado plot in Figure 38 was created. The plot shows that the most influential parameters were the utility cost from being in BMI groups above a healthy BMI, and the discount rate. The largest positive effect on net benefit came from reducing the discount rate, which increased the net benefit by £164.58 to £1,322.57. The largest negative effect on net benefit came from increasing the utility decrement of being in BMI groups above healthy BMI, which reduced the net benefit of the Slimming World programme by £163.32 to a net benefit of £994.67. The group of parameters with the smallest effect on net benefit was the mortality rate from disease.

Figure 38: A Tornado Plot of One-Way Sensitivity Analysis



When using a discount rate of 1.5%, the largest effect on cost-effectiveness was reported. Changing the discount rate to 1.5% resulted in an increase in QALYs gained to 0.076, whilst the cost-saving increased to £88.80 per person. The lifetime net benefit was found to be £1,600.18 per person. At 2-years and 6-years, the intervention remained cost-effective, but not cost-saving, with ICERs of £7,492.96 and £3,355.16 per QALY and net benefits of £167.57 and £377.33 per person at 2 and 6 years respectively. Intuitively, adjusting the discount rate only had a small effect at 2 and 6 years, but a larger effect on lifetime results as outcomes further in the future are affect most sensitive to changes to discount rates.

10.1.2 Probabilistic Sensitivity Analysis of the Base-Case

A probabilistic sensitivity analysis (PSA) was performed by running 10,000 Monte Carlo simulations with random draws from parameter distributions, including random draws for the coefficient values in regression models predicting weight-change each year. Table 76 shows the mean results of the

PSA across the 10,000 simulations of the base-case of effectiveness assumptions for a lifetime time-horizon.

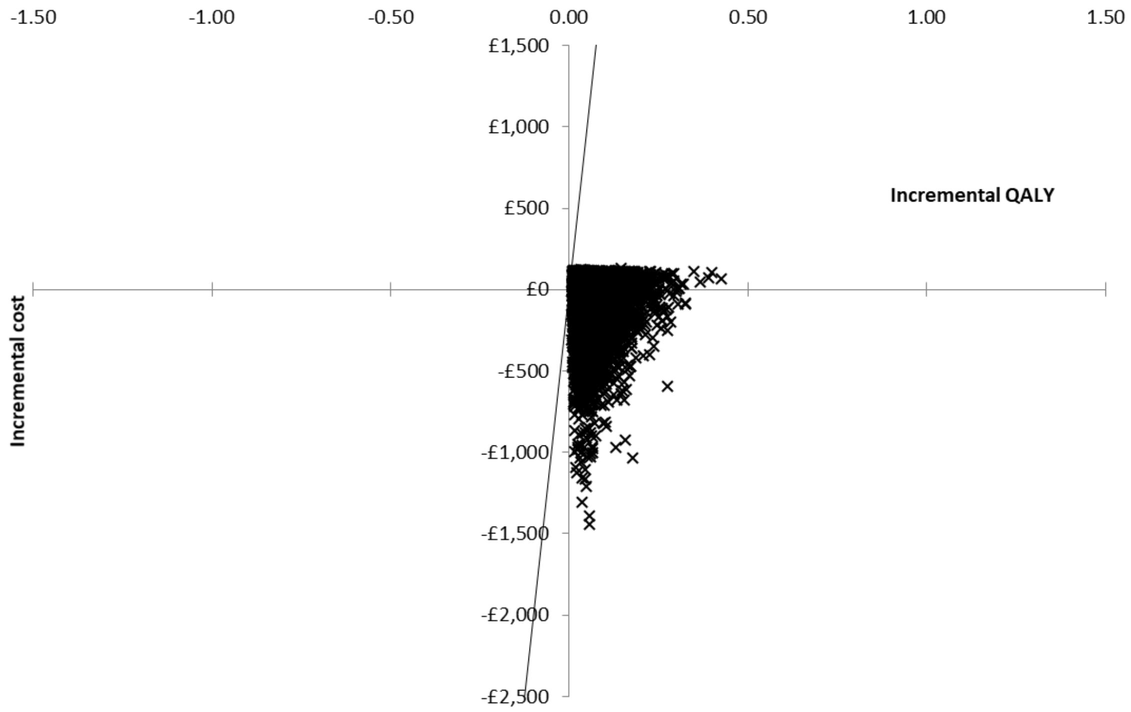
Table 76: Results of PSA on Cost-Effectiveness for the Base-Case

Outcome	Mean Value	Worst Outcome Values	Best Outcome Values
QALYs	0.0594	0.00742	0.427
Costs	-£42.04	£128.32	-£1,441.51
Cost per QALY	£508.68	£15,299.53	SW dominates
Net Benefit	£1229.74	£34.86	£9,046.76

The Slimming World programme provided a greater number of QALYs than the control group in each of the 10,000 simulations, with the minimum number of incremental QALYs provided being 0.007 per person. As well as providing a positive effect on QALYs in each simulation, the Slimming World programme was also cost-effective against a threshold of £20,000 per QALY in every simulation. The Slimming World programme was estimated to be cost-saving in 52.9% of simulations.

The incremental QALYs and costs of each of the 10,000 sets of random draws of parameter values were plotted in Figure 39, below, with the cost effectiveness threshold being plotted, and all 10,000 points being plotted to the right of the threshold.

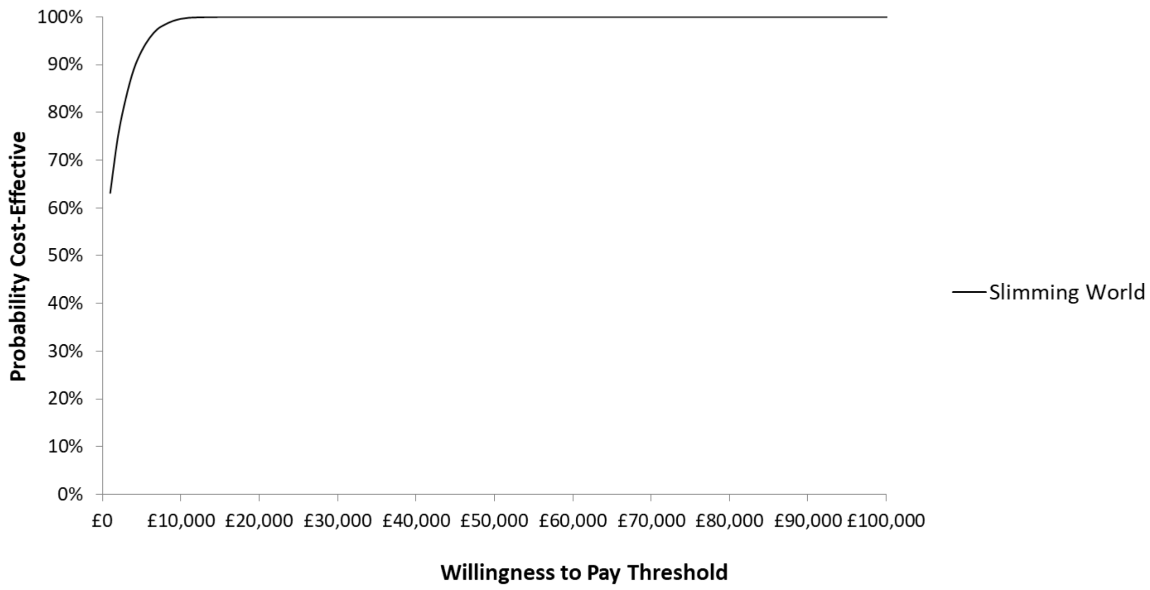
Figure 39: Cost-Effectiveness Plane in the Base-Case



As the intervention was cost-effective over the control group in 100% of cases, the value of information was estimated to be zero, as the intervention was the optimal choice in all 10,000 simulations.

Figure 40 shows the cost-effectiveness acceptability curve, which illustrates that at the threshold of £15,299.53 per QALY and above, the probability that the intervention is cost-effective over usual care is 100%, but this probability declines as the willingness to pay declines.

Figure 40: Cost-Effectiveness Acceptability Curve in the Base-Case



10.2 Alternate Weight-Trajectory Scenarios

Following analysis of the effect of PSA, the impact of adjusting the assumptions regarding effectiveness was investigated. The scenarios, taken from Chapter 9, were tested in turn and compared against the assumptions for weight-trajectories for the control group in the base-case. The base-case assumptions were judged to be the most plausible projections of weight-trajectories, and so the results from the alternative scenarios were compared with the base-case results, which is listed as scenario 1. The scenarios are listed again, below, with participants who regained all weight-loss reverting to matching the control group trajectory, and those who did not match the control group trajectory continuing at the background trajectory after weight-regain had occurred.

- Scenario 1 (base-case): Heckman-correction model weight-change projections at 2-years and meta-regression weight-regain model predicting regain up to year 6
- Scenario 2: Heckman weight-loss projections at 1-year for those who stopped attending before the end of the first year, and 2-years for those who continued attending. Those who dropped out before the first year regained weight up to year 3 as predicted by the Slimming World follow-

up study model, whilst those who continued attending regained weight to year 6 according to the meta-regression weight regain model.

- Scenario 3: LOCF weight-change at 2-years and weight-regain up to 6-years as predicted by meta-regression model.
- Scenario 4: LOCF weight-change at 1-year for those who dropped out before the end of the first year, and LOCF weight-change at 2-years for those who continued attending. Those who dropped out before the first year regained weight up to year 3 as predicted by the Slimming World follow-up study model, whilst those who continued attending regained weight to year 6 according to the meta-regression weight regain model.
- Scenario 5: BOCF at 1-year for those who stopped attending before 6-months and LOCF for those who stopped attending before 1-year, and LOCF at 2-years for those who continued attending past 1-year. Weight-regain from the meta-regression model up to year 6 for all.

Table 77, shows outcomes in terms of BMI at both 2-years and 6-years. Scenario 5, which assumed BOCF for those who stopped attending before 6-months, had the greatest proportion of obese and severely obese individuals at 2-years, which is expected as the assumptions in the first 2-years were the most conservative. Scenarios 3 and 4, which assumed LOCF weight-change as the measure of effectiveness in the weight-loss phase, had the lowest estimates of mean BMI, which is again expected as no regain was assumed to occur after dropout for these individuals.

Table 77: BMI Outcomes in Scenario Analysis

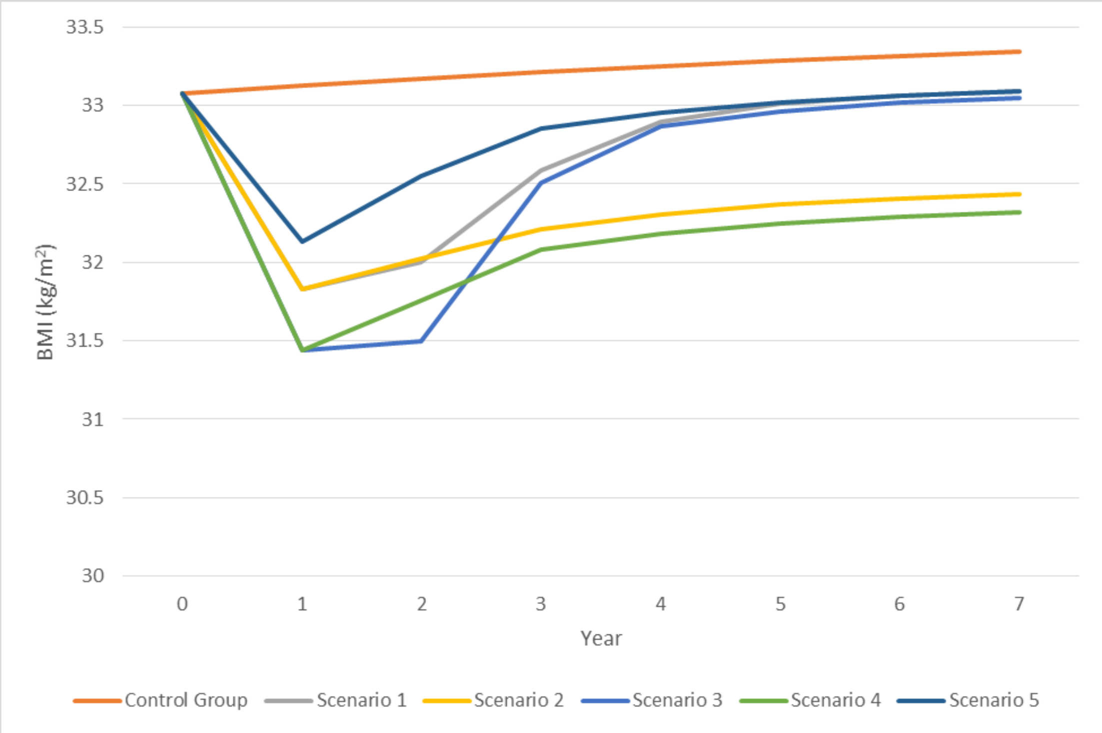
Scenario	Mean BMI (kg/m^2)	BMI >30kg/m^2	BMI >40kg/m^2
2-Year			
1 (base case)	32.00	58.33%	8.79%
2	32.03	57.91%	9.19%
3	31.49	52.49%	9.81%
4	31.76	54.78%	9.74%
5	32.55	59.92%	12.41%
6-Year			

1 (base case)	33.07	65.19%	12.97%
2	32.41	60.70%	10.60%
3	33.02	64.20%	13.11%
4	32.29	58.93%	10.89%
5	33.07	63.89%	13.36%

At year 6, scenarios 1, 3 and 5, which all took weight regain from the meta-regression weight-regain model, had the highest mean BMIs and proportion of obese and severely obese individuals. The meta-regression weight-regain model predicted a faster weight-regain than the Slimming World follow-up model, and was also implemented for a longer possible time-period, due to the follow-up model only having a maximum of 3-years of follow-up time. This helps to explain why the outcomes in scenarios 2 and 4 are more favourable in terms of BMI outcomes. The scenario analysis shows that at 6-years, the assumptions regarding weight-regain are more important that the assumptions about missing data in the weight-loss period.

Figure 41 shows the weight trajectories for each scenario of weight-change up to year 6, as well as the weight-trajectory in the control group. The figure illustrates the importance of weight-regain. When comparing scenario 2 and scenario 3, scenario 2 provides less weight-loss, with the mean BMI at 2-years being over half a BMI point lower. However, as scenario 2 assumes a slower rate of weight-regain, much of this weight-loss is maintained in the long-term, with the mean BMI in scenario 3 becoming greater before year 3. At year 6, the mean BMI in scenario 2 is over half a BMI point less than in scenario 3, and this difference is assumed to be maintained in the long-term as all participants continue on the background weight- trajectory after year 6, when the weight-regain period is assumed to have ended.

Figure 41: Weight-Change over Time for each Scenario



A summary of the outputs in terms of incremental QALYs, costs and cost-effectiveness is shown in Table 78, below, with the base-case again being shown for comparison. The table illustrates that all 5 scenarios were cost-effective at each time point, with net benefit increasing with the length of the time-horizon considered. As QALYs and costs were derived from BMI groups, similar results for BMI outcomes were seen in estimates of cost-effectiveness. Therefore, scenarios 2 and 4, which had the least weight-regain, both estimated the intervention to provide over £4,000 of net benefit per person, which was much greater than the net benefit estimated in scenarios 1, 3 and 5. This was possible despite scenarios 2 and 4 providing only the second least and second largest net benefit at 2-years – which marked the end of the maximum intervention phase. This illustrates the importance of long-term assumptions regarding weight-regain are for long-term estimates of cost-effectiveness.

Table 78: Results of Scenario Analysis on QALYs, Costs and Cost-Effectiveness

Scenario	Incremental QALYs	Incremental Costs	ICER	Net Benefit
2-Year				
1 (base case)	0.013	£100.63	£7,584.04	£164.74
2	0.013	£101.06	£7,714.50	£160.94
3	0.016	£95.30	£6,108.97	£216.70
4	0.015	£97.20	£6,567.57	£198.80
5	0.008	£109.01	£14,231.07	£44.19
6-Year				
1 (base case)	0.022	£77.78	£3,536.14	£362.15
2	0.034	£39.78	£1,159.77	£646.22
3	0.025	£69.25	£2,770.00	£430.75
4	0.038	£31.46	£836.70	£720.54
5	0.015	£88.52	£6,021.77	£205.48
Lifetime				
1 (base case)	0.056	-£36.47	SW dominates	£1,157.99
2	0.180	-£410.38	SW dominates	£4,010.38
3	0.072	-£82.21	SW dominates	£1,512.21
4	0.200	-£448.28	SW dominates	£4,448.28
5	0.062	-£58.95	SW dominates	£1,290.95

When only considering the initial 2-year and 6-year periods, Slimming World was not cost-saving under any scenario. Over the lifetime time-horizon, Slimming World was cost-effective in all scenarios. The pattern that presents across the cost-effectiveness estimates is that using LOCF weight-change provides the largest level of cost-effectiveness in the short-term (scenarios 3 and 4). Including the weight-regain observed in the Slimming World follow-up study of those who left the programme provided the largest level of cost-effectiveness in the long-term (scenarios 2 and 4). Together, these findings indicate that regain assumptions are more influential than assumptions regarding initial weight-loss for those who leave the programme when assessing cost-effectiveness with a lifetime time-horizon.

10.3 Testing Weight-Regain Scenarios used in Previous Economic Evaluations

As well as assessing realistic scenarios of weight-regain developed within this PhD, alternative assumptions about weight-regain, taken from the previous economic evaluations, reviewed in Chapter 6, were analysed. For each scenario, weight-change at 2-years came from the Heckman-correction model. Again, each scenario was run against the control group assumptions from the base-case. After weight-regain, participants joined the background weight trajectory. Outcomes were only assessed at the end of the full time-horizon, as 2-year outcomes were defined by the Heckman model in all scenarios, and weight-regain time-periods differ between scenarios. The scenarios are listed below:

- Scenario 6: No weight-regain
- Scenario 7: Annual decay of effect
- Scenario 8: Regain BMI points each year until the background rate was met
- Scenario 9: Linear regain over time to match the control group trajectory
- Scenario 10: Regain BMI points each year until baseline
- Scenario 11: Linear regain to baseline
- Scenario 12: Weight-regain defined by probabilities

Table 79 shows the range of results when reviewing various weight-regain assumptions from other economic evaluations was larger than identified earlier in the scenarios of weight-loss and weight-regain in Table 78. The net benefit from adjusting regain rates had a range of £4,871.33, compared with £3290.29 in the results in scenarios 1-5. Of the scenarios assessed, all seven were cost-effective, with four being cost-saving over the course of a lifetime. The scenario which provided the largest net benefit was scenario 6, which was as expected, as the scenario assumed no weight-regain, which meant the intervention group maintained the benefits from the weight-loss phase for the full time-horizon. The scenario which provided the least benefit was scenario 9. This was also to be expected as in this scenario a linear regain that matched the control group's weight at 5-years was assumed, and in this case, all no benefit remained after this time-point, unlike in the other scenarios. Scenario 8 was the only other scenario assuming regain to match the control group, but as the rate of regain was slow with participants only regaining 0.36 BMI points per year, at least some benefit to the programme remained after 20-years, which is why the net benefit in scenario 8 is greater. Scenarios 7 and 12 both provided lower net benefit that scenario 8, despite scenario 8 assuming a regain to match the control group. This was because in scenario 7, the decay of effect of 50% per year meant that the effect diminished quickly in the first two to three years, with the remaining effect diminishing slowly over time. In scenario 12, the majority of the sample regained all weight loss to the control group at 1-year, which lowered the potential for benefit in the long-term. The plausibility of the effect of adjusting assumption on outcomes helps to provide internal validation to the model.

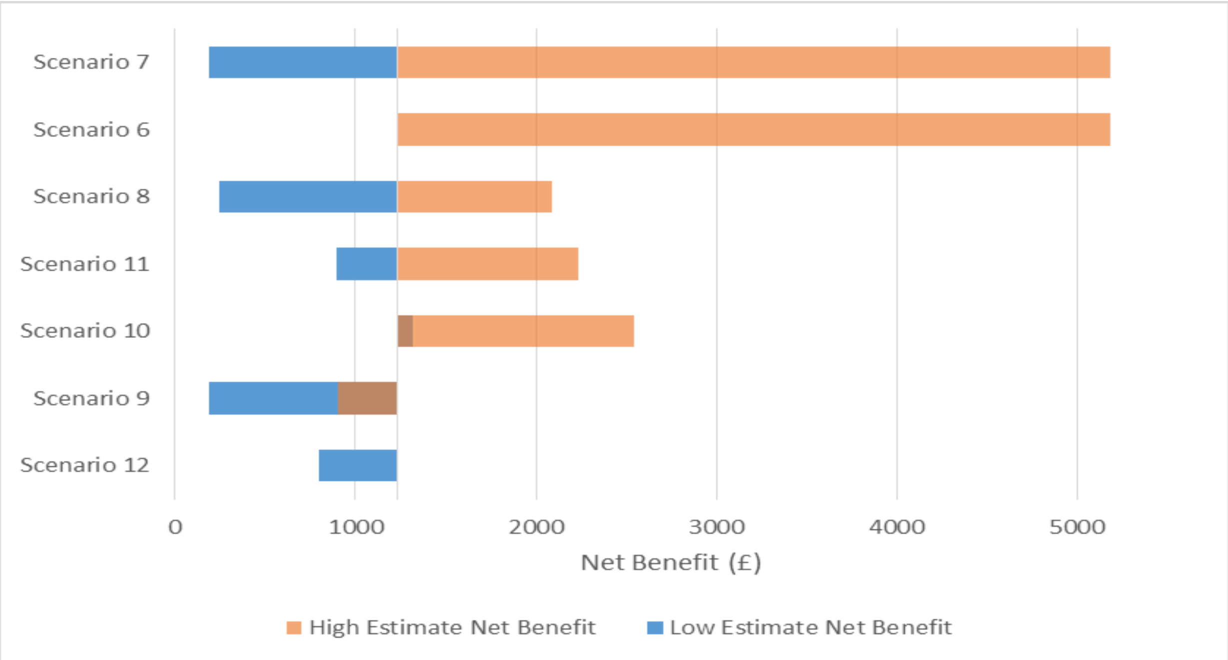
Table 79: Results of Scenarios Analysis with Scenarios from the Literature

Scenario	Incremental QALYs	Incremental Costs	ICER	Net Benefit
Lifetime				
1 (base-case)	0.056	-£36.47	SW dominates	£1,158.47
6	0.230	-£585.18	SW dominates	£5,185.18
7	0.037	£32.92	£894.57	£703.08
8	0.046	-£3.74	SW dominates	£917.74
9	0.020	£84.15	£4,228.64	£313.85
10	0.084	-£118.90	SW dominates	£1,792.90

11	0.048	£1.87	£39.12	£954.13
12	0.041	£13.80	£340.74	£796.20

When analysing the extreme values used in each of the scenario types, the net benefits over the course of a lifetime were identified and illustrated in the tornado plot in Figure 42. For scenarios 6 and 12, no alternative values were tested, and so the median value of net benefit was plotted. For scenario 9 both the low and high estimates were lower than the deterministic estimate of net benefit in the base-case, with the opposite being true for scenario 10. The tornado plot illustrates the impact of changing assumptions of weight-regain, with the ranges being much larger than the ranges identified in the one-way sensitivity analysis of model parameters. The lowest value of net benefit was £186.64 which was seen in both scenarios 7 and 9, where all weight-loss was regained in the first year after leaving the programme. The greatest net benefit was £5,181.34, which came from scenarios 6 and 7, where all weight-loss was maintained. The range of estimated net benefits was £4994.74.

Figure 42: Tornado Plot of Net Benefit of Various Scenarios



The ranges illustrate the problem with previous economic evaluations, and the assumptions regarding weight-regain. The low estimates of net benefit come from making the assumption that all individuals regain weight-quickly, with the high estimates of net benefit being derived from scenarios where either all individuals maintain the weight-loss, or they all maintain some weight-loss for a long-time before eventually regaining all weight-loss. In reality, it is more likely that different individuals regain weight-loss at different rates and that whilst the majority of individuals will regain their weight-loss, there are some individuals are able to maintain a permanent weight-loss, which is why applying different rates of regain for different individuals is important.

10.4 Adjusting the Control group Assumptions and Background Trajectories

Assumptions regarding the control group, and the weight-trajectories for individuals who did not participate in the intervention were tested to identify the importance of the assumptions. Table 80 shows the outputs for the alternative scenarios for the control group with control group scenario 1 being the scenario in the base-case. The alternative scenarios are shown in the list below:

- Control Group Scenario 2: Baseline weight was maintained for the first 2 years before joining the background weight-trajectory.
- Control Group Scenario 3: The control group lost 1kg at year-1 and maintained this weight-loss at year-2 before joining the background weight-trajectory.
- Control Group Scenario 4: Baseline weight was maintained for the first 6 years before joining the background weight-trajectory.

The analysis shows that holding weight constant during the intervention phase (control group scenario 2), and assuming baseline weight was maintained for the first 6-years (control group scenario 4) reduced net benefit, which is as expected considering the intervention provides a lower comparative effect over the control group. Assuming a 1kg weight-loss in the control group (control group scenario 3) further reduced the net benefit provided by the intervention, and meant the intervention was no longer cost-saving. This range of outcomes shows a relatively small impact of adjusting control group assumptions compared with adjusting assumptions of weight-trajectory in the intervention group, especially considering that a flat 1kg weight-loss per person maintained at 2-years would be a reasonably optimistic outcome for a control group in usual care.

Table 80: Outputs for Alternative Control Group Scenarios

Control Group Scenario	Incremental QALYs	Incremental Costs	ICER	Net Benefit
Lifetime				
1 (base-case)	0.0561	-£36.47	SW dominates	£1,158.47
2	0.0506	-£18.88	SW dominates	£1,030.88
3	0.0335	£30.90	£922.39	£639.10
4	0.0461	-£3.49	SW dominates	£925.49

10.4.1 Analysis of Adjustments to Background Weight-Trajectories

The final stage of analysis was to test the effect of changing assumptions about background weight-trajectories, to assess the importance of trajectories unrelated to the intervention. Table 81 shows the outcomes when adjusting background weight-trajectories. For all scenarios, is was assumed the intervention group followed the base-case assumptions until year-6, and the control group followed control group scenario 4 – so that both the intervention group and the control group joined the background weight-trajectory at year 6. Background scenario 1 used the background weight-trajectory in the base-case. The scenarios are listed below:

- Background scenario 2: No weight-change
- Background scenario 3: 1kg gain per year
- Background scenario 4: 0.429kg gain per year

When assuming no background weight-change after 6-years (background scenario 2), the estimated net benefit of the intervention increased, despite the difference between the BMI of participants in the intervention group and control group being constant. When considering a weight-gain of 1kg per year (background scenario 3), the opposite effect occurred; net benefit fell.

Table 81: Outputs for Alternative Background Trajectory Rates over a Lifetime

Background Scenario	Incremental QALYs	Incremental Costs	ICER	Net Benefit
Lifetime				
1 (control group scenario 4)	0.0461	-£3.49	SW dominates	£925.49
2	0.0506	-£18.88	SW dominates	£1,030.88
3	0.0333	£32.88	£987.39	£633.12
4	0.0398	£11.88	£298.49	£784.12

In background scenario 3, the increase in weight of 1kg per year resulted in the mean BMI of the intervention group being 51.76kg/m^2 at age 100 in compared with a mean BMI of 30.27kg/m^2 at age 100 for the intervention group in the base case. This was a result of the total number of QALYs in each cohort decreasing, as BMI in both groups was higher, leading to higher disease and mortality rates. Therefore, the total number of QALYs gained over the control group was reduced.

10.5 Alternative Programme Consideration

The alternative programme of 12-weeks was assessed to understand the outcomes if the effect of the 12-week GP referral was considered to be the intervention. When considering only the first 12-weeks of the Slimming World programme, and up to 4-years of regain, as assumed in the base-case, the intervention cohort gained 0.0244 QALYs on average over the course of a lifetime. The incremental cost was £51.63 per person which meant the intervention was cost-effective with an ICER of £2,116.10, which equated to a net benefit of £436.37. It was not cost-saving, in contrast to scenarios 1-5. It is understandable that this scenario is less cost-effective than scenarios 1-5 as all participants begin weight-regain after week 12 rather than continuing to lose weight. This meant that mean BMI was 32.96kg/m^2 at 2-years and 33.19kg/m^2 at years 2 and 6, which was the highest in all 5 scenarios.

At 2-years, the cost per QALY was £24,682.80, which gives a net benefit of -£21.83. This means that the programme is not cost-effective when only considering a 2-year time-horizon. At 6-years, the cost per QALY fell to £14,131.33, which was cost-effective against the £20,000 per QALY threshold. This shows that even when only considering the intervention to compromise of the initial 12-week programme, and instantly begin to regain weight, the intervention is cost-effective over a lifetime, although less cost-effective than when assuming up to two-years of weight-loss.

10.6 Probabilistic Sensitivity Analysis of Selected Scenarios

The scenarios assessed with probabilistic sensitivity analysis were assessed to view the range of outcomes that may come from providing the intervention. Each scenario was created using assumptions already analysed in this chapter, and combined into a new scenario of overall weight-trajectory, which are listed in Table 82.

Table 82: Selected Scenarios

Scenario	Weight-Loss	Weight-Regain	Background Rate
Best-Case	Scenario 3	Scenario 6	Background Scenario 2
Worst-Case	Scenario 5	Scenario 8 with control group matched at year-3	Background Scenario 3
Meads et al. (2014)	Base-Case	Scenario 6	Background Scenario 4

Probabilistic sensitivity analysis was performed on each scenario at both 6-years and for the full life time-horizon. For each of the scenarios listed in Table 83, to reduce computational burden, 1,000 iterations were run, rather than the lifetime base-case which had 10,000 iterations. The purpose of the PSA was to fully understand the range of outcomes possible from implementing the intervention.

Table 83 shows the results of the PSA. All scenarios were cost-effective in 100% of Monte Carlo simulations at the £20,000 per QALY threshold, other than the worst-case scenario after 2-years, with only 959 of the 1,000 scenarios reporting a cost-effective outcomes. However, at 6-years and over a full life-time, even the worst-case scenario was cost-effective in all simulations at both time-points. The best-case scenario and the scenario in Meads et al. (2014) were also cost-saving in over 99% of cases when considering the full lifetime time horizon, which is important in the current financial climate, with health care commissioners being under pressure to find affordable solutions to public health problems. In the base-case, which represents the most plausible outcome, there is still over a 50% likelihood that the intervention is cost-saving.

Table 83: PSA Outcomes for Selected Scenarios

Scenario	Mean Net Benefit	Min Net Benefit	Max Net Benefit	Probability Cost-Effective (%)	Probability Cost-Saving (%)
2-Year					
Base-Case	£149.58	£42.75	£149.58	100.0	0.0
Best-Case	£348.40	£102.61	£203.68	100.0	0.0
Worst-Case	£29.53	-£20.65	£99.68	95.9	0.0
Meads et al. (2014)	£149.58	£42.75	£149.58	100.0	0.0
6-Year					
Base-Case	£345.41	£59.82	£1,114.99	100.0	1.7
Best-Case	£920.50	£584.63	£1,524.38	100.0	34.2
Worst-Case	£125.96	£42.96	£234.55	100.0	0.0
Meads et al. (2014)	£730.54	£321.10	£1,245.10	100.0	20.6
Lifetime					
Base-Case	£1229.74	£34.86	£9,046.76	100.0	52.9
Best-Case	£6,661.72	£3,341.61	£11,019.88	100.0	99.9
Worst-Case	£527.75	£218.34	£1,024.44	100.0	22.6
Meads et al. (2014)	£4,387.35	£1,517.77	£8712.41	100.0	99.5

If these results are extrapolated to the full population of adults that are either overweight or obese, and it is assumed that the outcomes of the sample of 10,000 in the modelling is generalisable to the full population the impact of using more informed assumptions becomes clearer. It was estimated in the previous chapter that the population of adults that are overweight or obese in the UK is 42,518,714. If this is multiplied by the incremental QALYs gained per person of 0.056 per person, a total of 2,381,048 QALYs are gained with a cost saving of £1.55bn. When considering the best-case scenario, the total number of QALYs gained was estimated to be 12,755,614, with a cost-saving of £28.97bn. This shows the difference in projections that is possible, coming from different assumptions regarding unknown weight-change trajectories after individuals leave the weight-management programme.

10.7 Hypothetical Scenarios of Weight-Change and Weight-Regain

The final analysis was to assess cost-effectiveness outcomes for different combinations of initial weight-loss and different periods of time in which weight-loss is regained. Ten separate values for weight-change were used (0.5kg-5kg) and compared against ten separate values for time period of weight-regain (1-year to 10-years). The net benefit estimations for each of the 100 hypothetical scenarios are shown below in the two-way sensitivity analysis table in Figure 43. Participants regained weight to match the control group, with the control group following the background weight-trajectory from baseline. Each scenario is colour coded where red represents non-cost-effective scenarios, orange represents cost-effective scenarios and green represents cost-saving scenarios.

Figure 43: Two-way Sensitivity Analysis showing ICERs (£) for Varying Levels of Weight-Loss and Time for Weight-Regain

Weight-Loss (kg)										
0.5	-68	-53	-39	-23	-6	12	32	55	81	108
1	-32	-8	18	46	73	102	134	168	205	244
1.5	4	40	74	111	151	191	235	281	327	377
2	47	92	137	185	235	285	339	396	452	517
2.5	84	139	195	253	316	377	444	509	581	654
3	127	191	260	328	400	475	550	631	714	797
3.5	162	237	316	394	478	564	654	744	839	936
4	198	283	371	465	559	656	754	857	961	1072
4.5	231	327	426	529	633	741	853	968	1082	1205
5	264	371	481	592	707	829	950	1075	1203	1335
Regain (years)	1	2	3	4	5	6	7	8	9	10

The sensitivity analysis shows that the intervention is cost-effective in 93 of the 100 scenarios. Only the scenarios with small magnitudes of weight-loss and faster weight regain rates were not cost-effective over a lifetime. When considering a weight-regain time-frame of 6-years or more, even a 0.5kg weight-loss initially was sufficient to be cost-effective. If a 10-year weight-regain time-frame was assumed, the intervention was cost-saving in 4 of the 10 weight-loss scenarios.

10.8 Discussion

These analyses have demonstrated the importance of assumptions regarding long-term effectiveness when evaluating behavioural weight-management programmes. One-way sensitivity analysis assessing the impact of adjusting parameter values showed that estimates of QALYs and costs were robust to changing parameter values to realistic extremes, with the largest impact coming from adjusting the utility decrements from BMI and the discount rate. However, when adjusting weight-change scenarios, the impact on outcomes was much larger.

When varying the parameters inside the model one-by-one, estimates of cost-effectiveness were robust, with the largest impact of net benefit being an increase by £164.58 per person, and the range of net benefits being £327.90 (£994.67-£1,321.30). When assessing the impact of PSA on parameters including coefficients in the weight-change model, it was found that the intervention was cost-effective in all 10,000 Monte Carlo simulations. However, the range was much greater at £9,011.90 (£34.86-£9,046.76).

Scenario analysis found that by using LOCF weight-change, a greater weight-change was predicted at 2-years than the Heckman-correction model, whilst BOCF analysis predicted the lowest level of weight-loss. However, whilst using LOCF analysis for weight-change in the first two years did have a positive impact on cost-effectiveness, the rate of regain in the following period was much more influential in terms of lifetime cost-effectiveness, with the scenarios that had less or slower regain following the intervention period having much higher levels of net benefit. This highlights the importance of long-term weight-trajectories when modelling weight-change programmes. If a programme achieves a moderate weight-loss initially which participants are able to maintain, it may be more effective in the long-term than a large weight-loss with poor weight-maintenance. Therefore, programmes should be encouraged to follow-up participants of programmes in the long-term, and if possible provide assistance with weight-maintenance after the intervention has ended. Where follow-up is not possible, sensitivity analysis of weight-regain should be carried out extensively so that decision makers are able to understand the effects of various potential and plausible scenarios.

By performing analysis using the various scenarios of weight-regain taken from previous evaluations of weight-management programmes, the importance of using realistic and plausible assumptions of this regain was made clear, and seen by the large range in values for estimated QALYs and costs. The range of estimated net benefits was £4,994.74, with the range being the difference between assuming that all weight-loss is regained at year 3, and assuming that all weight-loss is maintained permanently. The range shows the importance of accurate assumptions regarding weight-regain, with largest effect on net benefit coming from changing assumptions regarding weight-regain in the intervention group.

NICE guidance for economic modelling of weight-management programmes stated that the largest limitation to modelling of weight-management programmes was the lack of evidence regarding weight-regain (Brown et al., 2013). Similar to the previous literature, the guidelines tested the same assumption for all individuals. A decay of effect each year was assumed, similar to the assumption used by Ginsberg and Rosenberg (2012) and Cobiac et al. (2010). However, the guidance used regain rates of 5%-40% regain per year, with little evidence for these assumptions. This shows that official guidance from NICE may have been poor information due to the basic assumptions made regarding weight-regain with little evidence.

Assumptions regarding weight-change in the control group had less effect on estimates of net benefit, but this was due to the smaller range of plausible scenarios. This is because control groups have less uncertainty regarding weight-loss and weight-regain. There is less need to test extreme scenarios as low-intensity ‘usual care’ interventions are unlikely to have a large mean impact across all individuals. Therefore, adjustments to control group assumptions do not drastically impact on estimates of net benefit, and modellers should prioritise making predictions regarding weight-trajectories in the intervention group.

Adjusting background weight-trajectory assumptions also had a limited effect on net benefit in comparison with assumptions about weight-regain. However, the range of effect was large, considering the constant difference between BMI in the intervention group and control group. This was due to unrealistic assumptions regarding weight-trajectory which undermined estimates of net benefit. Gaining weight indefinitely for the remainder of the lifetimes results in unrealistically large BMIs in older age, and inaccurate estimations of the QALYs in both groups. Modellers should ensure that background weight-trajectories are realistic and plausible, using information regarding weight-trajectories in population-level data.

When assessing the best- and worst-case scenarios of weight-change, even when assessing the worst-case scenario at 6-years, the programme was cost-effective in all of the 1,000 Monte Carlo simulations that were performed, and cost-saving in over 20% of cases over the course of a life-time. In the best-case scenario, the intervention was cost-saving in 99.9% of cases.

In terms of the effects on the Slimming World programme, Slimming World was cost-effective in all 10,000 of the scenarios in PSA of the base-case, and cost-saving in more than half. This suggests that policy makers can be confident that the Slimming World programme is a value for money investment in the long-term. Even when only considering weight-loss in the first 12-weeks, and with the regain phase beginning immediately after, the Slimming World programme was cost-effective over usual care. The scenario analysis also showed that the programme was cost-effective at 2-years in all 5 scenarios, which again can provide policymakers with confidence that the money invested will see a return in terms of QALYs in the short-term.

When considering that the only cost of the intervention is the payment for the referral to Slimming World initially, the estimation that the programme is cost-effective after two-years, is promising, especially when considering only the first 12-weeks of attendance are funded, and Slimming World participants are willing to self-fund to attend. The results show that commercial behavioural weight-management programmes such as Slimming World have great potential as a low-cost primary care strategy to reduce obesity prevalence, with the intervention often being cost-saving, and even cost-effective when only considering short time-horizons.

In summary, cost-effectiveness programmes, the analysis and sensitivity analysis in this chapter have shown that assumptions regarding weight-regain are the most important factor in assessing the cost-effectiveness of weight-management programmes. The next chapter will discuss how this PhD has addressed the questions set out at the beginning, and the recommendations made in light of the findings.

Chapter 11: Discussion

The aim of this chapter is to discuss the PhD as a whole. This chapter will first present the research problem and the research questions that were set out in the opening chapter. The chapters in this PhD will then be discussed, alongside their findings, and how these findings contribute to answering the research questions and addressing the overall aim of this thesis. These findings will then be placed within the literature. The strengths and weaknesses of the research will be presented, before the suggestions of future research are made. Finally, the recommendations for future economic evaluations will be made in light of the findings in this PhD.

11.1 The Research Problem

The problem that this thesis aimed to address was the issues with long-term weight-trajectories following behavioural weight-management programmes, and how economic evaluations should attempt to address these issues when modelling cost-effectiveness. This was an important research topic as long-term trajectories after these weight-management programmes are unobserved, as observations are usually recorded when participants attend the programme during the intervention phase. As only the intervention period is observed in these programmes, and economic evaluations should model long-term outcomes, it is important that weight-management programmes correctly model long-term weight-trajectories.

The overall aim of this PhD was make recommendations for the improvement of the best practice for modelling the cost-effectiveness of weight-management programmes. These recommendations were made through testing various scenarios of weight-trajectories following weight-management programmes to illustrate the effect that errors in assumptions can have on estimates of cost-effectiveness.
The following discussion will address how the findings answered the following five research questions, which were set out in Chapter 1:

1) Which economic and behavioural economic theories explain how individuals behave in regard to weight-management?

2) Are the hypothesis made by the theoretical framework reflected in real world data?
3) How have economic evaluations been modelled in the past?
4) What weight-trajectories can be expected following the completion of weight-management programmes?
5) What is the impact on cost-effectiveness of adjusting assumptions regarding long-term weight-trajectories?

11.2.1 Theoretical Framework of Weight-Management

To identify economic and behavioural economic theories of weight-management, a systematic review of the literature was performed in Chapter 2. When analysing the data in the identified papers, three themes of theories emerged in the literature to explain weight-management behaviour – rational choice, time-preference, and habits and self-control. Under these three themes, a theoretical framework was developed, in Chapter 3, to explain why individuals may rationally choose to be obese, why individuals may decide to sacrifice their long-term weight-management goal for short-term impulse, and why it may be difficult for individuals to be able to continue with weight-management successfully. The hypotheses made using the theoretical framework were used to build a regression model to predict weight-change within the case study of the Slimming World programme.

11.2.2 The Slimming World Data

This PhD used the commercial weight-loss programme Slimming World as a case study for analysis, with Slimming World providing a dataset of members and outcomes for the purpose of this research. The theoretical framework created in Chapter 3 was used to inform the variables that were used in the regression modelling for the Slimming World data. In general, the hypotheses made regarding the influence of variables on weight-change were reflected in the Slimming World data, although causality is unknown and these relationships may have occurred for other reasons. This was shown by the agreement between the expected influence from the theoretical frameworks, and the signs of the coefficients in the regression models.

Because the sample size was so large, even very small differences were significant at the 5% level. Therefore, when reviewing the influence of variables, coefficients were assessed on whether they had a meaningful effect on weight-change, rather than solely statistical significance.

In the rational choice framework, a larger target weight-loss, less income deprivation, a greater starting weight, joining through a referral and attendances all had a significant positive effect on weight-loss, as predicted by the framework. Education also predicted increased weight-loss, although the magnitude of this impact was small, and when included in multivariate regression, predicted slightly less weight-loss. This may have be due to education and skills IMD level being a poor proxy for knowledge. It was assumed that those living in areas with a greater level of education and skills deprivation would be less able to process information provided to them and convert this into healthy behaviours. However, whilst this measure may be able to broadly represent the area, the difference in ability to process information by individual is likely not well captured.

An individual having diabetes was estimated to achieve less weight-loss, which was opposite to the hypothesis, although again this effect was small in magnitude. Diabetic status was included to represent a health shock, and that an individual who had received this health shock may have been more motivated to lose weight. However, it may be that individuals who are diabetic are less able to lose weight due to dietary and physical activity restrictions. Finally having a partner, children and full-time over part-time employment were included in the model. However, as these were judged to be poor proxies for the amount of free-time available, and as there was a large amount of non-random missing data involved with these variables, they were not included in analysis.

From the time-preference framework, both a greater BMI and an older age were found to be significant predictors of weight-loss, which was in line with the hypotheses made by the framework. The framework also hypothesised both education and diabetes would predict a greater weight-loss, although, as discussed earlier, neither of these yielded strong effects on weight-change.

In the habits & self-control framework, individuals who were more overweight at the start of the programme were hypothesised to have worse weight-management behaviours to their strong habits in relation to eating. However, this was found to be not reflected in the real world data, as individuals who were heavier were estimated to lose more weight. This hypothesis was made by the rational choice framework though, where those who were more overweight were expected to lose more weight due to an increased motivation due to being further from their ideal weight. This means that the higher level of motivation from being more overweight enables individuals to overcome poor behaviours in regards to weight-management, but in the long-term, these individuals may have more difficulty maintaining weight-loss. The habits & self-control framework did however correctly predict the influence of the different join-types on weight-loss. The framework hypothesised that those who rejoined the programme would lose less weight than those who had never been Slimming World members before, and that those who joined via a countdown would lose more than other members due to the long-term financial commitment made upon joining the programme.

Due to the theoretical framework being able to identify influential variables in regards to weight-change, the theories were able to be used to create predictions of weight-loss for individuals that left the Slimming World programme, to inform model building when analysing evidence of follow-up, and when predicting long-term weight-trajectories using the ELSA data.

Overall, the regression models created using these theories were found to be significant predictors of weight-loss when tested. Weight-loss for all participants of the case study programme was established using regression modelling techniques informed by economic and behavioural economic theories. As the drop-out rate in obesity interventions is so high, it is important to review the outcomes of all individuals and not only those who complete as drop-out may not be random, and so the outcomes are likely to be biased (Moroshko et al., 2011). By establishing predictors of weight-management behaviour, regression models made projections of weight-change that fell between BOCF imputed values and LOCF imputed values. The method of estimating weight-change for individuals improves upon using BOCF analysis as BOCF implies that for those that leave the programme, which is the vast majority, weight-management interventions do not provide any weight-loss, which is overly conservative (Kaiser et al., 2012). The methodology in this PhD also improves upon LOCF analysis, which in weight-management programmes is likely to produce an overly optimistic estimate of effectiveness (Papp et al., 2008).

11.2.3 The Current Literature on Economic Evaluations of Weight-Management

To assess the current literature on economic evaluations in weight-management, a systematic review of the literature was undertaken. This review was an update of Griffiths et al. (2012), with a greater focus on cost-analysis in the evaluation of behavioural weight-management programmes. Economic evaluation is a tool to facilitate the allocation of scarce resources (Caro et al., 2012). However, long-term outcomes of interventions are often unobserved, and need long-term modelling to capture the potential outcomes in terms of costs and effects. When considering longer-term horizons, as economic evaluations for preventative care should, predicting weight-regain becomes a fundamental piece of analysis. NICE provides guidance on lifestyle weight-management interventions, and states that ideally cost-effectiveness should be assessed over at least 10-years (NICE, 2014). Improving the accuracy of cost-effectiveness estimates is especially important in the current financial climates due to the funding cuts to public health care in the United Kingdom (The King's Fund, 2019). This means that now more than ever, health care commissioners must be confident that the new interventions they fund are value for money. The review found that previous decision models evaluating the cost-effectiveness of weight-management programmes have made simplistic assumptions in regards to weight-regain, as shown in Chapter 6. The assumptions are often not grounded in theory or based on evidence, and the analyses often do not test alternate scenarios. In some cases, no weight-regain following the programme was assumed (Smith et al., 2016). Generally, the cost-effectiveness models all assumed an identical method of weight-regain for each individual, rather than, for example, using individual characteristics, the number of attendances an individual made, or the amount of weight-loss an individual experienced to make predictions of weight-regain (Ahern et al., 2017; Meads et al., 2014). Instead, evaluations made more broad assumptions such as all individuals regaining all weight-loss within a certain number of years, all individuals regaining a fixed amount of weight per year, or a percentage decay of effect for all individuals (Thomas et al., 2017; Hoerger et al., 2015; Ginsberg and Rosenberg, 2012).

Despite long-term weight trajectories being a large unknown, past economic evaluations performed little sensitivity analyses to establish cost-effectiveness under alternative scenarios of post-programme weight-change. The ISPOR-SDSM Modelling Good Practices Task Force states that where long-term time-horizons are used for evaluation, and outcomes must be extrapolated beyond the available data, sensitivity analysis should be performed (Roberts et al., 2012). It is necessary also that this sensitivity analysis tests both upper and lower bounds of potential outcomes (Roberts et al., 2012). This is especially true in the case of weight-management intervention outcomes, as long-term weight-maintenance is unpredictable and is characterised by significant uncertainty (Hall and Kahan, 2018).

Due to uncertainty, these limited assumptions can lead to inaccurate projections regarding long-term weight-trajectories. This, in turn, can lead to inaccurate estimates of cost-effectiveness for the weight-management programmes. By investing in interventions that have errors in their methodology, it can lead to an inefficient allocation of resources, which can mean resources are reallocated from other, more cost-effective, healthcare interventions (Tan-Torres Edjeder, 2003).

As well as weight-regain assumptions often being basic, past economic evaluations mostly did not use appropriate assumptions when considering background weight-trajectories, which should be applied to both the intervention group and the control group after the weight-regain phase. It is important that a model represents reality as accurately as possible (Vemer et al., 2016). By making unrealistic assumptions of long-term weight trajectories, reality is not reflected. By assuming that weight is constant over time, this ignores that humans experience weight-change as they age, whilst also assuming a constant rate of weight-regain each year results in individuals having extremely large BMIs by the end of the time-horizon. Neither of these approaches represent what happens in the real-world, and so external validity of weight-change projections comes into question (Eddy et al., 2012).
As bodyweight and BMI are the key drivers of health effects in the economic models, it must be ensured that the weight-trajectories are accurate, as these

weight-trajectories define the effect of the intervention. As weight-maintenance is a key issue in ensuring the long-term effectiveness of weight-management programmes, as specified by NICE guidance, economic evaluations should put a greater focus into ensuring the problem is modelled correctly (Squires et al., 2016; NICE, 2014).

11.2.4 Evidence of Weight-Regain

The literature was searched for evidence of long-term follow-up weight-change observations after behavioural weight-management programmes, as data regarding long-term weight-change is generally unobserved in real-world weight-management programmes. Following weight-management programmes, the research in this PhD found that on average, individuals regain weight after leaving the weight-loss programme, with weight regain occurring at a declining rate over time. It was also found that because of the declining rate of weight-regain, participants of weight-loss programmes on average did not regain weight to baseline, and were therefore able to maintain some weight-loss. This pattern was evident in both the meta-regression model built using a systematic review of the literature, and a regression model built using data from a follow-up study of Slimming World programme participants.

These findings were consistent with a systematic review of randomised controlled trials of dieting programmes (Mann, 2018). With weight-change behaviour, the reasoning behind decision making is complex, with many potential influencers. One reason is that individuals who need to lose weight initially are likely to have bad habits regarding weight-management. After these individuals have lost weight and been dieting for a long-time, they eventually will succumb to temptation and eventually revert to their old habits, which will cause weight-regain, and a trend towards their pre-weight-loss weight (Cleo et al., 2017). The alternative reason is biological, with the human body wanting to be at a set weight, and adjusting hormones and metabolism in an attempt to return to the physiological equilibrium (Ochner, 2013).

Furthermore, participants who lost more weight were expected to regain more weight, but still maintain a greater weight-loss over individuals who lost less weight when weight-regain flattened. Again, this pattern is consistent with previous literature (Sawamoto et al., 2017; Bacahar et al., 2018). A systematic review of predictors of weight-loss maintenance found initial weight-loss was a positive predictor of weight-loss maintenance in 71.4% of cases, with the remaining 28.6% of cases being non-significant and 0% being negatively predictive (Varkevisser et al., 2018).

Another finding was that the majority of weight-regain came initially after leaving the programme, with the rate of weight-regain declining over time. A follow-up study of a sample of Slimming World members, undertaken by Slimming World, was also analysed to assess long-term weight-trajectories after leaving the programme, with similar results of weight-regain to the meta-regression model. Although the meta-regression model predicted greater weight-regain, the pattern of weight-regain, with the rate of regain slowing over time and participants maintaining some weight-loss was also predicted by the regression model built using the Slimming World follow-up study. These two sources of data on weight-trajectories post-programme were used to inform weight-regain in the cost-effectiveness model after the initial 2-year weight-loss phase at Slimming World. By using these sources, weight-regain rates in the decision model were defined by data from studies on behavioural weight-management programmes, with the magnitudes of regain depending upon individual characteristics, attendance, and weight-change within the intervention. By using this method, heterogeneity in effect was captured in predictions of weight-regain, rather than assuming an identical parameter value for all individuals. As discussed earlier, individuals who lose more weight, regain more weight, but are able to maintain a greater weight-loss. As well as this, being older and being male predicted greater success with weight-loss maintenance, and this was backed up by the literature (Varkevisser et al., 2018). The implications for these findings is that weight regain is varies by person, and economic modelling should reflect this heterogeneity seen in the real-world. Behavioural weight-management programmes can also learn from these findings and offer more support to subgroups that struggle to maintain weight-loss, whilst policymakers can target subgroups who are more successful with weight-loss maintenance, as interventions targeted at these subgroups should be more cost-effective.

11.2.5 Background Weight-Trajectories

After the initial weight-regain following the weight-management programme had flattened, participants returned to background weight-trajectories that they would have followed if they had not been involved in an intervention. To reflect reality appropriately in the model, a dataset of bodyweight and BMI observations from the English Longitudinal Study of Aging, which has not been used in previous decision models evaluating weight-management programmes before, was analysed to create trends for weight-change over time. A regression model was built to predict weight-change each year for the individuals within the economic model. By building background weight-trajectories, realistic weight-trajectories for individuals in the control group, who did not receive the intervention, and for individuals after weight regain had flattened were created. Again, these trajectories were based on real-world data from the general population and created more valid projections when compared with previous economic evaluations (Eddy et al., 2012).

This improved upon much of the current economic evaluations where often, no background weight-trajectory was assumed, which meant that participants maintained the same weight for the remainder of their lives (Gray et al., 2018; Smith et al., 2016). Another common assumption was that individuals gained a fixed amount of weight per year, which meant that by the end of the model all individuals had very high BMIs, which is not clinically plausible (Trueman et al., 2016; Lewis et al., 2014).

11.2.6 Cost-Effectiveness Modelling and Testing Weight-Trajectory Assumptions

By bringing together theory, systematic literature reviews and evidence synthesis, econometric analyses and decision-analytical modelling, this PhD has been able to establish a more plausible scenario of long-term weight-change for participants of behavioural weight-management programmes. In the modelling in Chapters 9 and 10, the assumptions made regarding weight-trajectories in previous economic evaluations were tested against the base-case created in this PhD.

Adjusting assumptions and parameter values regarding weight-trajectories was found to be the key influencer of estimates of cost-effectiveness by varying all parameters in the cost-effectiveness model. This is because the weight-regain assumption determines how long individuals in the intervention group receive the benefit of being in a lower BMI group and lower disease risk. If it is assumed that individuals regain weight-loss instantly, they only receive the benefits of weight-loss for the intervention period. However, if it is assumed that weight-loss is not regained, the individuals receive the benefits for the remainder of their life. Therefore, basic assumptions of weight-regain in decision modelling can lead to large errors in estimates of cost-effectiveness.

As these previous economic models have had flaws in their methods, it implies that previous weight-management programmes and guidance have been poorly informed by these models. NICE guidance regarding economic modelling of weight-management programmes acknowledges the importance of weight-regain assumptions but then proceeds to use assumptions with little evidence to support them, testing scenarios of a decay of effect between 5% and 40% (Brown et al., 2013). In the open source model offered by Public Health England (2016), the model also uses very basic assumptions of weight-regain. The model predicts a flat increase in weight of 0.56kg per year for all individuals until participants reach baseline, at which the individuals remain at baseline weight for the remainder of the model. This evidence is taken from Johns et al. (2013), which identified the regain rate as 0.56kg per year from a review of studies with follow-up up to 1-year. This means that even in guidance regarding the modelling of cost-effectiveness from Government bodies, long-term weight-trajectory assumptions are extremely basic, and somewhat arbitrary.

11.3 Strengths and Weaknesses

The key strength to this PhD is that multiple approaches have been used to inform modelling, with both theory and evidence providing insight. For weight-trajectories within the model, projections have been made using information from the literature on economic and behavioural economic theories of weight-management, real-world data in a large-dataset from a weight-management programme, and evidence from the literature and population-level datasets regarding long-term weight-trajectories in both weight-management programme participants and individuals in the UK. Once these approaches were combined to making overall weight-trajectories for individuals, the resulting weight-trajectories were plausible and passed validity tests.

This study has used a large dataset from a real-world commercial weight-management programme – Slimming World, with members coming from all demographic groups and from all over the United Kingdom, which means the outcomes are generalisable to a UK setting. As weight-management interventions are not administered in controlled environments, and focus on behavioural change when individuals are in the real-world, results from observational studies are also more generalisable to real-world (Hebert et al., 2016). As well as using real-world data for participants and weight-loss, weight-regain and background weight-trajectories were also defined by real world data, which improves the validity of estimates.

An extensive range of sensitivity analyses was performed in regard to weight-change trajectories. By testing assumptions from past-economic evaluations, this PhD has explored the impact of these assumptions on cost-effectiveness, and the large differences that are possible. As the base-case in this study is defined by real-world data and is a more informed and sophisticated projection of weight-change trajectories, the estimates of cost-effectiveness are able to illustrate the difference in estimates of cost-effectiveness compared with using basic assumptions.

Finally, the transparency of this study is another strength. Transparency in economic modelling is important so decision makers can understand the process behind modelling and the assumptions that have been made (Kent et al., 2019). This PhD has explained each stage of the model adaptation process and all the features of the cost-effectiveness model, where predictions come from, and the sources of the information.

In the Slimming World case-study, there were no defined limits on the time period assessed by Slimming World. Individuals that joined the Slimming World programme were able to attend for as long as they wanted to continue attending, which means that some individuals that are assumed be regaining weight in the cost-effectiveness model after 24-months may still be members of the Slimming World programme and losing weight. Not having defined limits, as well as individuals being able to come and go from the programme as they choose, also meant that individuals needed to be grouped into periods of time when they left the programme, in order to not overly complicate analysis. However, sensitivity analysis was performed where only the first 12-weeks of attendance at the Slimming World programme, as well as testing the impact of BOCF and LOCF analysis. In all cases weight-regain still had a larger effect on life-time cost-effectiveness than the weight-loss assumptions. As well as this, costs were largely based on assumptions, with the cost-effectiveness analysis including all costs in analysis, when in fact the majority of costs come from out-of-pocket payments by participants who join Slimming World without any intervention. Another limitation of the study was that this study still relied on assumptions rather than observed data, which limits the certainty of estimates of cost-effectiveness, and the ability to illustrate error with predictions of cost-effectiveness in the literature.

A further limitation in the study was that predictions of weight-regain in both the meta-regression study and Slimming World follow-up study were based on individuals who were willing to be followed up in the long-term. This introduced the potential for bias, as individuals who respond to follow-up may be more willing to respond if they have successfully maintained their weight-loss (Holzapfel et al., 2013, Hammer et al., 2009). Another limitation with these sources of weight-regain data was that both had reasonably low sample sizes, which limits the confidence in the evidence provided, and in the meta-regression, few studies followed up participants over 4 years into the future. Ideally, evidence regarding weight-regain would have a large number of studies with very high response rates to follow-up and long-time frames for follow-up.

The final key limitation of this study is that the analysis did not use a discrete event simulation model. This is because in the Markov model, all individuals entered the model at the same age, and individuals were only able to transition to different BMI groups and health states each year, for simplicity. In simulation models, individual patient histories can be captured which would mean that event probabilities could depend on previous BMIs and past-disease states, whereas in Markov models event probabilities only depend on the current state, which is limiting as the probabilities are based on more limited information about the individual (Standfield et al., 2014). As well this, Markov model health states are mutually exclusive, which is a simplification. The solution to this was creating co-morbidity health states, but this complicates the model as each combination of health states must be a separate health state. If a simulation model was used, it would have been able to incorporate more diseases which would have improved the accuracy of estimates of effectiveness. In the Markov model, individuals also could only be in one of 5 BMI groups, and individuals moved through the model each year depending on probabilities of transitioning from one BMI group to another. In a simulation model, individuals could be traced, and individuals specific outcomes could be analysed, rather than an estimate of total outcomes based on the number of people in each BMI group each year.

However, there were advantages to using a Markov model rather than a discrete event simulation model. The first of these was that a simulation model would have required a much larger amount of data to incorporate all the various interactions between diseases, the ability to use patient history, and the continuous transitions, rather than transitions each year (Almagooshi, 2015). A simulation model would have also required much more computational time, and when running many iterations of probabilistic sensitivity analysis on a sample of 10,000 individuals over a lifetime, this would have been problematic, due to the computational needs. Overall, Markov models are regarded as an appropriate modelling choice for weight-management programmes, and the Markov model used in this PhD is able to incorporate various assumptions regarding weight-trajectories, and effectively illustrate the impact of adjusting these assumptions, which suits the overall aim of the PhD.

11.4 Future Research

Future research should aim to identify trends in public health behaviours, and how well behaviour can be maintained. Both NICE guidance on weight-management programmes, and the literature on physical activity, have agreed that maintenance of effect is the key-driver of cost-effectiveness, but literature regarding maintenance of effect is limited (Brown et al., 2013, Gc et al., 2019). Studies should aim to follow-up participants of behavioural weight-change interventions in the long-term, in order to gain an insight into how well their participants are able to maintain weight-loss, and understand whether they need to better equip their participants with weight-maintenance strategies.

NICE guidelines suggest that a focus should be put on improving outcomes with regard to weight-regain but little research is available on long-term outcomes (Brown et al., 2013). If following up participants becomes more common for behavioural weight-management programmes, the currently small amount of existing literature regarding long-term weight-change would be improved upon, which would create for more comprehensive body of literature on the subject. Having comprehensive reviews of the long-term outcomes of weight-management programmes would vastly improve the ability to make accurate of estimates of weight-regain trajectories, and would therefore improve the accuracy of cost-effectiveness estimates, and decision making. Studies should also research the value of this information (Tuffaha et al., 2014).

Another line of research is spill over effects within households. If participants of weight-management programmes are parents and spouses, then improved behaviours in regards to eating and physical activity are likely to have an effect on other members of the household. If participants of weight-management programmes are followed up in the long-term, questions regarding eating habits at home can be asked to identify whether changes to the parents behaviours have impacted their children. If weight-management programmes are able to improve behaviours towards eating, this may, in turn, improve the diets and health of children. Future research should consider these spill over effects in economic evaluations, and the effect that weight-regain has on them (Al-Janabi et al., 2015).

Future research could also use individual level modelling dis-aggregating estimates of cost-effectiveness by subgroups of interest. By identifying cost-effectiveness estimates for specific subgroups, policymakers may be better able to target interventions, as they are better informed of the likely impacts of the intervention on these subgroups of interest. Health care commissioners have the aim of maximising health in the area, and by identifying which interventions are most cost-effective for which subgroups, commissioners are better able to optimise their spending to maximise health (NHS England, 2019). Information regarding effects would therefore allow policymakers to focus funding on individuals who would receive the most benefit from the intervention to maximise the use of resources.

Clinical Commissioning Groups in the UK have a key priority of reducing inequalities, and will therefore be aware of the inequalities in health outcomes in the local population and understand which groups require attention (Buck and Maguire, 2015). If a commissioner has a specific target to achieve, such as to improve health outcomes in men, or to improve health in low-income households, it can be useful to have specific information regarding the effect of an intervention on the targeted sub-group. For example, individuals with low-incomes may not have enough disposable income to spend on attending commercial weight-management programmes. If health care providers were informed about the potential effects of providing free programmes for individuals with low-incomes, they may be able provide solutions to this problem and contribute to closing the gap in health between the least and most privileged in society. If policymakers do not have this information, they may be reluctant to employ targeting of policies due to the large uncertainty of outcomes. Distributional cost-effectiveness analysis is a framework used to include health inequalities into economic evaluation, and could be used to inform local decisions regarding referrals to weight-management interventions (Asaria et al., 2016).

As well as policymakers being better informed regarding the targeting of interventions, GPs may also be aided by disaggregated results. For example, with referral programmes, a GP may see a commercial weight-loss programme as a weight-loss solution aimed at women, as the vast majority of participants tend to be women, and therefore be reluctant to refer male patients. However, men within the Slimming World programme perform better than women. If GPs are aware of the benefits the programme provides specifically to men, it may encourage more referrals to male patients. Knowing this may also mean the marketing of these programmes would be better targeted at men.

To achieve cost-effectiveness estimates by subgroup, future research would require information regarding weight-loss, weight-regain, and long-term weight-trajectories for individuals in these specific sub-groups. This would be required in order to make accurate projections of future weight-trajectories for the given sub-group. Costs and benefits for the sub-group would then be derived from the projected weight-trajectories to provide cost-effectiveness estimates specific to the chosen subgroup. As well as this, the decision model would require inputs specific to the chosen subgroup, for example disease rates and outcomes. By using these, the model would be able to produce a best-estimate of cost-effectiveness. Whilst this research would be useful, there is little information about long-term weight-regain in the current literature, and it would therefore be difficult to be able to identify weight-regain trajectories for specific subgroups. Assumptions based on the general population would therefore have to be made regarding weight-regain, which would limit the usefulness of subgroup analysis. Sensitivity analysis could assess hypothesised realistic ranges of parameter values to provide some insight into potential effects on subgroups however.

Other subgroups of interest could be those with physical or mental health problems caused by BMI. For example, individuals who have suffer from diabetes, or have had a stroke in the past may behave differently to healthy individuals following weight-management programmes. Similarly, individuals who have a bad relationship with food and suffer from mental health problems because of it may also behave differently in regards to weight-regain. These are the most at-risk groups and being able to improve the accuracy of estimates of outcomes in these individuals could possibly provide the most immediate benefit to health.

11.5 Recommendations

This PhD has provided valuable insight into the effect of post-programme weight-trajectory assumptions on cost-effectiveness, and shown how weight-trajectories following the programme are the most influential driver of the cost-effectiveness of behavioural weight-management programmes. Economic evaluations should ensure that projected weight-trajectories are well thought out and represent real-world possibilities, checking the validity of these projections against real-world data. Evaluations should put more focus on including more sophisticated projections regarding weight-trajectories. In order for healthcare commissioners to gain a full understanding of the potential outcomes before making any funding decisions, various possible outcomes when considering missing data, including worst-case scenario analysis, should be considered.

Obesity has health implications and more evidence is needed of the long-term effectiveness and cost-effectiveness of weight-management programmes. Weight-management programmes should seek to follow-up participants in the long-run to improve the depth of the current evidence on long-term weight-change outcomes after behavioural weight-management programmes.

The findings from the PhD were combined into a recommendations table, in Table 84, designed to provide guidance to economic modellers aiming to make estimates of the cost-effectiveness of a behavioural weight-management programme.

By following these recommendations, modelling practice will be improved, which should lead to more accurate evidence being generated, and better decision making. Expanding the evidence base will allow for more informed estimates of the long-term effectiveness and cost effectiveness of these programmes which in turn will allow policymakers to make more informed decisions when allocating funding in regard to obesity.

Table 84: Recommendations for Economic Modelling

Area of Study	Recommendation	Comments
Choice of Model	Markov models are appropriate for analysis Simulation models should also be considered	Markov and patient-simulation models are able to capture time which is important in weight-management as there is no end-point for health risk
Missing Data	Values for individuals who drop out of weight-management programmes should be predicted controlling for attendance	BOCF should be avoided as it is overly conservative whilst LOCF should be avoided as it is overly optimistic Where prediction is not possible, LOCF may be considered for very short-term programmes, whilst BOCF should be used for long-term programmes
Weight-Regain	Weight-regain should be predicted using regression modelling with data sourced from evidence of weight-regain from similar weight-management programmes Sensitivity analysis should be performed assessing both lower and upper bounds of parameter values for weight-regain	Weight-regain rates are the key driver of estimates of cost-effectiveness and modelling should devote enough time to ensuring they create robust, valid estimates for this parameter Sensitivity analysis must be performed to highlight the range of possibilities in outcomes
Background Weight-Trajectories	Background weight-trajectories should be taken from population-level datasets	The purpose of background weight-trajectories is to reflect the reality of weight-trajectories in the real-world
Control Group	If a control group is not available, control groups should be a matched sample of individuals to the intervention group	Individuals in the hypothetical control group should be assumed to have the weight-trajectories they would have if no intervention was offered

Sub-Groups	Where possible, subgroups should be modelled separately	Subgroups should be modelled separately as it has been shown that different groups have different weight-management behaviours This is not a crucial, but may improve the potential targeting of programmes
Testing of Weight-Prediction Models	Weight-prediction models should first pass the face validity test, with weight-trajectories appearing to be plausible Weight-regain patterns in the model should be compared with the literature on weight-regain to assess whether the model predicts similar outcomes to the literature on weight-regain after weight-management programmes Weight-trajectories should be compared with population trends in the country of origin	Predictions should be compared with evidence to assess whether the model predicts similar outcomes to the literature on weight-regain after weight-management programmes, and general weight-trajectories associated with population trends
How to report	The modelling process should be presented alongside a description of the Markov Trace Cost-effectiveness predictions should be presented over a lifetime horizon alongside results from probabilistic sensitivity analysis Worst-case and best-case outcomes should also be presented	This is so policymakers understand the range of outcomes that are possible in order to have the ability to make the most informed decision

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Appendix

Appendix 1: Data Extraction Summary Table

Paper	Theory	Formula	Short Description	Evidence
Anand and Gray (2009)	Rational Choice	N/A	Utility from bodyweight influenced by society.	None identified
Buscemi et al. (2014)	Habits and Self-Control	N/A	Individuals that find food reinforcing need to engage in reinforcing substitute activities.	Those who had more frequent engagement with food-free activities lost most weight.
Cavaliere et al. (2014)	Time-Preference	N/A	Weight will only be managed if the utility from the discounted future wellbeing outweighs the current satisfaction from not managing weight.	Positive and significant relationship found between time-preference and BMI.
Cawley (2004)	Rational Choice	S+L+O+T+H = 24 hours S: sleep, L: leisure, O: occupation, T: transport, H: home production	Daily time constraint (SLOTH model) where individuals must allocate hours to 5 separate activities.	None identified
Courtemanche et al. (2014)	Time-Preference	$\max_{\mathbf{f}} \mathbf{U}(\mathbf{f}) - \mathbf{pf} + \boldsymbol{\delta} \mathbf{V}'(\mathbf{f})$ f: food consumption, U: utility, p: prices, $\boldsymbol{\delta}$: discount rate, V: utility in period 2	Two-period model food consumption affects present utility and weight in the second period, with decisions being based on individual discount rates.	Found strong evidence of a relationship between time-preference and BMI.
Djawadi (2014)	Habits and Self-Control	N/A	Framework of medical non-persistence which states that once losses have been compensated and individual will likely stop treatment early.	Found in an investment game that players played a safe option until losses were compensated and then switched to a risky option.
Dodd (2008)	Time-Preference, Habits and Self-Control	N/A	Sophisticated consumers aware of their time-preference and can set up mechanisms to alter future payoffs.	None identified
Dragone (2009)	Habits and Self-Control	$V(c(t), \dot{c}(t)) = U(c(t)) - \alpha \frac{\dot{c}(t)^2}{2}$	Model of eating behaviour where a change in eating behaviour has a cost	None identified

		V: future utility, C(t): food consumption, $\dot{c}(t)$: food consumption after change, U: utility, α: marginal disutility of changing food intake	attached with the cost depending on the magnitude of the change and the strength of the individual's habits.	
Dragone and Savorelli (2012)	Rational Choice	$\mathbf{U_{i,G}(c_i, w_i) = c_i\left(c_i^F - \frac{c_i}{2}\right) - \frac{1}{2}\left(w_i - w_i^H\right)^2 - \frac{\beta}{2}(w_i - w^G)^2}$ U: utility, i: individual, G: society, c: consumption, w: weight, F: energy, H: health	Model of eating behaviour where utility depends on food and bodyweight, with the utility from bodyweight depending on the healthy bodyweight and societal preferences.	None identified
Drewnowski and Darmon (2005)	Rational Choice	N/A	Food is chosen based on taste, cost, convenience, health and variety with diet based on awareness, motivation and food choices.	Healthier foods cost more meaning a healthier diet may be unaffordable for low-income groups.
Drewnowski and Specter (2004)	Rational Choice	N/A	Energy-dense foods are cheap which promotes overconsumption of energy for low-income groups.	Low-income households spend 18.7% of income on food and cannot allocate more to buy healthier foods.
Fan and Jin (2013)	Time-Preference, Habits and Self-Control	N/A	Time-preference affects how individuals evaluate costs and benefits. Hyperbolic discounters discount irrationally with preferences changing depending on which time period the individual is in.	Individuals with obesity showed significant difference between intended weight-loss and actual behaviour. Low self-control associated with poor eating and exercise behaviours.
Finkelstein et al. (2004)	Rational Choice	N/A	Individuals weigh up costs and benefits of	None identified

			every option alongside their preferences and constraints. Current environment leads to sub-optimal decision making from the perspective of society.	
Grunert et al. (2012)	Rational Choice, Time-Preference	N/A	Utility is maximised to preferences and constraints with informed consumers better able to do so. Food decisions often made with limited information and time so people make choices out of habit. Older people face more immediate threat to health from obesity and are therefore more motivated to manage weight.	None identified
Hruschka (2012)	Rational Choice	N/A	Deprivation results in overconsumption of energy as the cheapest foods are the most energy dense. Local stores in deprived areas may not stock healthy foods either. Obese may be sorted into deprived areas due to biased work and educational systems.	Relationship found between deprivation and obesity.
Jeffery (2012)	Time-Preference, Habits and Self-Control	N/A	Behaviour producing rewards/punishments likely to be repeated more frequently/less often. Delayed consequences are given a lower weighting to immediate ones.	Increasing financial incentives improves weight loss outcomes, reducing incentives worsens outcomes.
Just and Payne (2009)	Rational Choice	N/A	In situations where time is sparse individuals do not have time to make a fully informed decision and have to rely on heuristics.	None identified
Lim and Bruce (2015)	Habits and Self-Control	N/A	Many eating behaviours are suboptimal and habitual. People are loss averse and prefer to avoid weight gain than losing weight.	Individuals found to place same loss-averse to weight as monetary outcomes.

O'Neil et al. (2015)	Rational Choice	N/A	Those with economic stress have poorer access to food and can result in poor behaviours. Spousal support can encourage healthy eating.	Stress linked to poorer weight decisions for wives but not husbands.
Pampel et al. (2012)	Rational Choice	N/A	Higher socio-economic status groups have a larger cost associated with being obese due to longevity advantage.	Negative relationship between BMI and socio-economic status.
Richards and Hamilton (2012)	Rational Choice, Time-Preference	N/A	Equilibrium weight higher than ideal so rational to be overweight as weight not only source of utility. Rational addiction theory states utility from present consumption increases with increased stock of past consumption	None identified
Rosin (2012)	Habits and Self-Control	$E=(1+\alpha)(t)\delta)e(d,C^d)$ E: disutility from dieting, t: number of weight loss diets, d: duration of diet, α(t): additional effort needed for repeated dieting, δ: binary variable for if individual has dieted in the past, C^d – minimum quantity of calories consumed	Individuals plan out diet periods with increased duration and energy deficit requiring more willpower. Each additional diet requires more willpower than the last. Sophisticated individuals appreciate their behaviours change with time, naive individuals do not.	None identified
Ruhm (2012)	Rational Choice, Habits and Self-Control	Deliberative system: $Max_{f,c}$ U(W(f), f, c) subject to c + pf = I f: food consumption, c: other consumption, U: utility, W: weight, p: price, I: income	Dual decision theory with a rational deliberative system that analyses costs and benefits. Affective system acts on impulses. Decisions are made with conflicting inputs from each system.	None identified
Sundermacher (2012)	Rational Choice	λ_i (t, HS_{it} ,HS_{it-1i}, X_{it}) =P(T_i=t│T_i>t, H_{it}, HS_{it-1}, X_{it}) λ_i: conditional probability of behaviour change, t: time period, HS: health shock, i: individual, X_{it}: vector of	Rational addiction is the theory that present utility increases for each extra unit of past consumption. Model of health shocks assumes individuals learn about their actions when they have a health shock	Literature found no evidence of health shocks on behaviour change for individuals who were overweight.

		covariates summarising observed differences at t	which forces a behaviour change.	
Zukiewicz-Sobczak et al. (2014)	Rational Choice	N/A	'Poverty paradox' exists because deprived individuals cannot afford to eat healthily and overconsume energy due to cheap energy dense foods being the bulk of their diet.	None identified

Appendix 2: Data Extraction Forms for Empirical Evidence Papers

Paper (Author/ Year)	Main Findings
Ailshire et al. (2012)	Large US database found those in society that were most disadvantaged gained more weight than higher social classes over-time, with most of the difference being in early life.
Barlow et al. (2016)	Systematic review of time-preference literature found moderate evidence of a significant link between discounting and the risk of overweight and obesity.
Bimbo et al. (2015)	Having a supermarket in the neighbourhood linked to improved diet quality and a lower obesity prevalence rate.
Celnik et al. (2012)	An increased number of households with both partners working has meant that both partners have less free time. This has led to a reduction in average cooking time and an increase in the use of ready meals and takeaways which has contributes to an overconsumption of energy.
Drewnowski (2012)	Found in the US those with lower education and income had a greater obesity prevalence rate. Factors contributing to this were found to be the affordability of healthy foods and having a supermarket in the local area. Low property values predicted bodyweights for women better than education and income. In summary deprivation had a large impact on obesity.
Drewnowski et al. (2015)	Property values in the US were able to predict obesity, but not 1-year weight change. No other measures of socio-economic status were able to predict 1-year weight change.
Guerra et al. (2015)	5.5 year-long study in Switzerland on a cohort of people that financial difficulties were positively associated with weight gain.
Hashemi et al. (2015)	More immediate forms of payments caused a significant increase in participation in a weight loss programme.
Morris (2013)	Found a positive and significant effect of food desert intensity on obesity prevalence. However, it was small in magnitude.
Pan et al. (2012)	US data found that those that had been most stressed about being able to afford healthy meals over the last 12 months were significantly more likely to be obese than those who hadn't faced the same level of food insecurity.
Saba et al. (2014)	Found that in Italy, obese respondents to a survey were significantly less interested in nutritional information than their non-obese peers.
Seward (2014)	Low-income groups in the US found to have a lower desire to lose weight, and attempted less weight loss attempts than less deprived groups.
Sturm and An (2014)	Increase in the obesity prevalence rate in the US coincided with an increase in leisure time.
Sun (2016)	Found that in a study to find the optimal weight of a person that it was greater than the health maximising weight for both females and males.

Zeng et al. (2015)	Found that there was an ambiguous effect of food deserts on body weight.

Appendix 3

Join Type	N	N (%)
Standard	307,465	47.1
Re-Join	144,447	22.1
Countdown	63,875	9.8
Discount	119,786	18.3
Referral	17,896	2.7

Appendix 4

Attendance in Time-period	Count	Proportion (%)
Up to 3 Months	692,945	100.0
3 Months - 6 Months	309,881	44.2
6 Months - 12 Months	167,578	23.9
12 Months - 24 Months	81,902	11.8

Appendix 5: Rational Choice Variables and Proxies

Theory	Ideal Variable	Proxy Variable
More overweight means more motivation to lose weight	How much weight the individual is above ideal weight	Distance between baseline weight and target BMI
More disposable income means less barriers to weight loss	Budget constraint	Income IMD quintile
More free time means more time to diet/exercise	Free hours per week	Full-time/part-time work, partner at home, children at home
More deprived individuals may have supportive partners to help individuals manage weight	How supportive the individual's partner is	N/A
More societal discrimination more to gain from losing weight	How much discrimination the person receives	Distance between baseline weight and healthy BMI of 25
More information means better equipped to lose weight, and better information processing	Knowledge of weight loss of the individual	Attendances where the individual did not leave early, education IMD, diabetic and referral

Appendix 6: Time-Preference Variables and Proxies

Theory	Ideal Variable	Proxy Variable

Those that put more emphasis on the present find it more difficult to lose weight	Discount rate	Education IMD quintile, age
Those with greater risk to their health in the present will have more motivation to lose weight	Probability of health event	Age, diabetic
Hyperbolic discounters lose less weight	Hyperbolic discounter	Education IMD quintile, age

Appendix 7: Habits and Self-Control Variables and Proxies

Theory	Ideal Variable	Proxy Variable
Individual's with weaker habits are better able to lose weight	Strength of habits	Re-join membership and distance between baseline BMI and healthy BMI of 25
Replacing overeating with an alternative activity means more weight loss	Alternative activity dummy	N/A
Those that invest more in the programme initially should continue for longer	Payments, travel cost	Interaction between join type and income IMD quintile
Those that are sophisticated about self-control problems should lose more weight	Sophisticated dummy	Countdown
Each successive weight loss attempt is more difficult than the last	Number of past weight loss attempts	Re-join membership
Those with a higher stock of past consumption should find it harder to lose weight	Stock of past-overeating	Distance between baseline BMI and healthy BMI of 25

Appendix 8: Table 23 with Categorical IMD Variables

Variable	n	Coefficient	t-statistic

Target Weight Change (kg)	554,300	0.0216***	45.37
Income IMD Quintile 0 (0 most deprived, 4: least deprived)	509,926	-	-
Income IMD Quintile 1	509,926	-0.0947***	-6.92
Income IMD Quintile 2	509,926	-0.167***	-12.31
Income IMD Quintile 3	509,926	-0.232***	-17.08
Income IMD Quintile 4	509,926	-0.218***	-15.46
Partner at Home (1=yes, 0=no)	252,321	-0.393***	-28.45
Children at Home (1=yes, 0=no)	252,321	-0.0720***	-5.83
Employment Status (1=part-time, 0=full-time)	252,321	-0.119***	-9.01
Diabetic (1=yes, 0=no)	692,945	-0.362***	-15.17
Full Attendances	692,945	-0.513***	-530.93
Education and Skills IMD Quintile 0 (0: most deprived, 4: least deprived)	516,796	-	-
Education and Skills IMD Quintile 1	516,796	-0.0705***	-5.52
Education and Skills IMD Quintile 2	516,796	-0.129***	-10.01
Education and Skills IMD Quintile 3	516,796	-0.118***	-8.97
Education and Skills IMD Quintile 4	516,796	-0.0578***	-4.05
Age at Start Date (years)	692,945	-0.121***	-45.90
Join Type (re-join=1, standard=0)	451,912	1.891***	211.14
Join Type (countdown=1, standard=0)	371,340	-0.127***	-9.65
Join Type (discount, standard=0)	427,251	0.491***	47.81
Join Type (referral=1, standard=0)	325,361	-0.472***	-19.85

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

Appendix 9: Table 24 with Categorical IMD Variables

Variable	n	Coefficient	t-statistic

Target Weight Change (kg)	554,300	0.0225***	62.14
Income IMD Quintile (0: most deprived, 4: least deprived)	509,926	-	-
Income IMD Quintile 1	509,926	-0.0318**	-3.01
Income IMD Quintile 2	509,926	-0.0447***	-4.28
Income IMD Quintile 3	509,926	-0.0755***	-7.21
Income IMD Quintile 4	509,926	-0.0762***	-7.00
Partner at Home (1=yes, 0=no)	252,321	-0.120***	-11.58
Children at Home (1=yes, 0=no)	252,321	-0.120***	-13.03
Employment Status (1=part-time, 0=full-time)	252,321	-0.00421	-0.43
Diabetic (1=yes, 0=no)	692,945	0.0586**	3.19
Full Attendances	692,945	-0.0880***	-61.73
Education and Skills IMD Quintile (0: most deprived, 4: least deprived)	516,796	-	-
Education and Skills IMD Quintile 1	516,796	-0.0117	-1.19
Education and Skills IMD Quintile 2	516,796	-0.0344**	-3.48
Education and Skills IMD Quintile 3	516,796	-0.0290**	-2.86
Education and Skills IMD Quintile 4	516,796	-0.0250*	-2.28
Age at Start (years)	692,945	0.00632***	30.78
Join Type (re-join=1, standard=0)	451,912	1.189***	171.26
Join Type (countdown=1, standard=0)	371,340	0.473***	48.42
Join Type (discount, standard=0)	427,251	0.494***	65.36
Join Type (referral=1, standard=0)	325,361	0.458***	26.37

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

Appendix 10: Table 25 with Categorical IMD Variables

Variable	Coefficient	t-statistic
Target Weight Change	0.0192***	45.36
Income IMD Quintile	0	.
Income IMD Quintile 1	-0.0492***	-3.67

Income IMD Quintile 2	-0.0810***	-5.10
Income IMD Quintile 3	-0.133***	-7.57
Income IMD Quintile 4	-0.162***	-8.40
Diabetic	0.342***	15.25
Full Attendances	-0.109***	-61.10
Total Attendances	-0.517***	-296.51
Education and Skills IMD Quintile	0	.
Education and Skills IMD Quintile 1	0.00707	0.54
Education and Skills IMD Quintile 2	0.0148	0.95
Education and Skills IMD Quintile 3	0.0361*	2.09
Education and Skills IMD Quintile 4	0.0361	1.87
Age at Start Date	0.00486***	17.88
Standard Join Type	0	.
Rejoin Join Type	1.140***	107.17
Countdown Join Type	0.371***	31.54
Discount Join Type	0.385***	38.85
Referral Join Type	0.315***	16.24
Baseline Weight	-0.0299***	-132.27
Male	-1.125***	-64.23
Constant	3.672***	151.47
N	393,318	

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

Appendix 11: Table 26 with Categorical IMD Variables

Variable	Coefficient	t-statistic
Target Weight Change	0.0195***	35.01
Income IMD Quintile 0	0	.
Income IMD Quintile 1	-0.114***	-6.46
Income IMD Quintile 2	-0.217***	-10.39
Income IMD Quintile 3	-0.322***	-14.00

Income IMD Quintile 4	-0.363***	-14.35
Diabetic	0.337***	11.42
Education and Skills IMD Quintile 0	0	.
Education and Skills IMD Quintile 1	0.0396*	2.28
Education and Skills IMD Quintile 2	0.101***	4.94
Education and Skills IMD Quintile 3	0.187***	8.25
Education and Skills IMD Quintile 4	0.270***	10.66
Age at Start Date	-0.0155***	-43.82
Standard Join Type	0	.
Rejoin Join Type	1.818***	131.07
Countdown Join Type	-0.154***	-10.03
Discount Join Type	0.297***	22.86
Referral Join Type	1.818***	-17.93
Baseline Weight	-0.0343***	-115.91
Male	-1.286***	-56.78
Constant	0.393***	12.82
N	393,318	

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

Appendix 12: Table 27 with Categorical IMD Variables

Variable	Coefficient (model 1)	t-statistic (model 1)	Coefficient (model 2)	t-statistic (model 2)
Target Weight Change	-0.0000719	-0.21	-0.000567*	-2.35
Income IMD Quintile 0	0	.	0	.
Income IMD Quintile 1	0.0131	1.18	0.0394***	5.14
Income IMD Quintile 2	0.0105	0.80	0.0801***	8.82

Income IMD Quintile 3	0.0162	1.13	0.110***	11.02
Income IMD Quintile 4	0.0240	1.52	0.121***	11.01
Diabetic	0.0113	0.63	0.00985	0.78
Full Attendances	0.0217***	17.21	.	.
Total Attendances	0.546***	281.14	.	.
Education and Skills IMD Quintile 0	0	.	0	.
Education and Skills IMD Quintile 1	-0.00874	-0.80	-0.0285***	-3.77
Education and Skills IMD Quintile 2	0.0223	1.74	-0.0455***	-5.10
Education and Skills IMD Quintile 3	0.0264	1.87	-0.0793***	-8.03
Education and Skills IMD Quintile 4	0.0308	1.95	-0.127***	-11.53
Age at Start Date	0.00125***	5.73	0.0105***	68.11
Standard Join Type	0	.	0	.
Rejoin Join Type	0.0861***	9.51	-0.361***	-57.65
Countdown Join Type	0.0531***	5.94	0.212***	32.21
Discount Join Type	0.0445***	5.51	0.0404***	7.21
Referral Join Type	0.124***	8.41	0.426***	38.90
Baseline Weight	0.000413*	2.24	0.00207***	16.09
Male	0.0156	1.15	0.0914***	9.38
Constant	-5.278***	-215.00	-0.936***	-69.89
N	393,318		393,318	

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

Appendix 13: Table 28 with Categorical IMD Variables

Variable	Coefficient (12-Weeks)	t-statistic (12-Weeks)	Coefficient (6-Monts)	t-statistic (6-Months)	Coefficient (1-Year)	t-statistic (1-Year)
Target Weight Change	-0.000145	-0.42	-0.000310	-0.98	0.0000261	-0.08
Income IMD Quintile 0	0	.	0	.	0	.
Income IMD Quintile 1	0.0315**	2.89	0.0509***	5.05	0.0257*	2.24
Income IMD Quintile 2	0.0572***	4.44	0.0906***	7.61	0.044**	3.26
Income IMD Quintile 3	0.0849***	6.00	0.111***	8.51	0.0607***	4.09

Income IMD Quintile 4	0.0960***	6.17	0.132***	9.16	0.0699***	4.29
Diabetic	-0.0305	-1.66	-0.0180	-1.15	-0.00555	-0.33
Full Attendances	0.0572***	42.51	0.0815***	67.88	0.0596***	27.83
Total Attendances	0.463***	286.03	0.241***	43.41	0.109***	15.64
Education and Skills IMD Quintile 0	0	.	0	.	0	.
Education and Skills IMD Quintile 1	0.00630	0.59	-0.0150	-1.52	0.00446	0.4
Education and Skills IMD Quintile 2	0.0239	1.89	-0.00938	-0.81	-0.0153	-1.17
Education and Skills IMD Quintile 3	0.0420	3.00	-0.0123	-0.96	-0.0141	-0.97
Education and Skills IMD Quintile 4	0.0482	3.10	-0.0206	-1.44	-0.0267	-1.65
Age at Start	0.00554***	25.40	0.00834***	40.99	0.00778***	29.05
Standard Join Type	0	.	0	.	0	.
Rejoin Join Type	0.0126	1.48	-0.125***	-14.58	-0.133***	-12.51
Countdown Join Type	0.0858***	9.47	-0.00930	-1.15	0.0100	1.13
Discount Join Type	-0.0152	-1.89	-0.0536***	-7.35	-0.0487***	-5.89
Referral Join Type	0.0282	1.84	-0.192***	-14.99	-0.0422**	-2.95
Baseline Weight	0.00134***	7.33	0.00204***	12.24	0.000901***	4.78
Male	0.0344*	2.49	-0.00554	-0.46	-0.0415**	-3.1
Attendance after 12-Weeks	-	-	0.467***	10.71	0.181***	3.65
Attendance after 6-Months	-	-	-	-	1.209***	22.53

Constant	-4.532***	-204.49	-4.165***	-120.52	-3.548***	-69.33
N	393,318		393,318		393,318	

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

Appendix 14: Selection Output for the Heckman Correction Model Predicting Weight-Change at Week 11

Variable	Coefficient	t-statistic
Attendance at Week 11		
Target Weight Change	-0.0000719	-0.21
Income IMD Quintile	0.00532	1.44
Diabetic	0.0113	0.63
Full Attendances	0.0217***	17.20
Total Attendances	0.546***	281.17
Education and Skills Quintile	0.00961**	2.58
Age at Start Date	0.00124***	5.71
Standard Join Type	0	.
Rejoin Join Type	0.0860***	9.50
Countdown Join Type	0.0530***	5.93
Discount Join Type	0.0445***	5.52
Referral Join Type	0.124***	8.42
Baseline Weight	0.000413*	2.24

Male	0.0156	1.15
Constant	-5.281***	-219.81
mills		
lambda	2.420***	128.75
N	393,318	

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

Appendix 15: Table 29 with Categorical IMD Variables

Variable	Coefficient	t-statistic
Target Weight Change	0.0351***	39.03
Income IMD Quintile 0	0	.
Income IMD Quintile 1	-0.107***	-3.67
Income IMD Quintile 2	-0.181***	-5.26
Income IMD Quintile 3	-0.260***	-6.87
Income IMD Quintile 4	-0.310***	-7.45
Diabetic	0.291***	6.63
Full Attendances	-0.107***	-34.66
Education and Skills IMD Quintile 0	0	.
Education and Skills IMD Quintile 1	0.0299	1.05
Education and Skills IMD Quintile 2	0.0786*	2.33
Education and Skills IMD Quintile 3	0.109**	2.91
Education and Skills IMD Quintile 4	0.158***	3.79
Age at Start Date	0.0107***	18.85
Baseline Weight	-0.0463***	-96.12
Male	-1.439***	-41.73
Constant	-1.114***	-19.39
Selection Output		
Attendance at Week 11		
Target Weight Change	-0.0000719	-0.21
Income IMD Quintile 0	0	.
Income IMD Quintile 1	0.0131	1.18
Income IMD Quintile 2	0.0105	0.80
Income IMD Quintile 3	0.0162	1.13
Income IMD Quintile 4	0.0240	1.52
Diabetic	0.0113	0.63
Full Attendances	0.0217***	17.21

Total Attendances	0.546***	281.14
Education and Skills Quintile 0	0	.
Education and Skills Quintile 1	-0.00874	-0.80
Education and Skills Quintile 2	0.0223	1.74
Education and Skills Quintile 3	0.0264	1.87
Education and Skills Quintile 4	0.0308	1.95
Age at Start Date	0.00125***	5.73
Standard Join Type	0	.
Rejoin Join Type	0.0861***	9.51
Countdown Join Type	0.0531***	5.94
Discount Join Type	0.0445***	5.51
Referral Join Type	0.124***	8.41
Baseline Weight	0.000413*	2.24
Male	0.0156	1.15
Constant	-5.278***	-215.00
mills		
lambda	2.420***	128.72
N	393,318	

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

Appendix 16: Table 30 with Categorical IMD Variables

Group	N	LOCF Weight-Change (kg)	OLS Model Prediction of LOCF Weight-Change (kg)	Heckman Correction of Weight-Change at Week 11 (kg)
Full Sample	393,318	-3.499 (3.167)	-3.499 (2.230)	-6.111 (1.300)
Attended Week 11	155,230	-5.376 (3.340)	-5.357 (1.340)	-6.409 (1.323)
Did Not Attend Week 11	238,088	-2.275 (2.346)	-2.288 (1.824)	-5.917 (1.247)

*standard deviation in parentheses

Appendix 17: Selection Output for the Heckman Correction Model Predicting Weight-Change at 6-Months

Variable	Coefficient	t-statistic

Attendance after 12-Weeks		
Target Weight Change	-0.000146	-0.42
Income IMD Quintile	0.0244***	6.66
Diabetic	-0.0305	-1.66
Full Attendances	0.0572***	42.50
Total Attendances	0.463***	286.08
Education and Skills Quintile	0.0135***	3.68
Age at Start Date	0.00554***	25.42
Standard Join Type	0	.
Rejoin Join Type	0.0125	1.46
Countdown Join Type	0.0857***	9.45
Discount Join Type	-0.0153	-1.91
Referral Join Type	0.0280	1.82
Baseline Weight	0.00134***	7.33
Male	0.0344*	2.49
Constant	-4.530***	-209.70
mills		
lambda	-0.590***	-33.19
N	393,318	

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

Appendix 18: Selection Output for the Heckman Correction Model Predicting Weight-Change at 1-Year

Variable	Coefficient	t-statistic
Attendance after 6-Months		
Target Weight Change	-0.000304	-0.97
Income IMD Quintile	0.0317***	9.42
Diabetic	-0.0179	-1.15
Full Attendances	0.0815***	67.84
Total Attendances	0.241***	43.40
Education and Skills Quintile	-0.00337	-1.00
Age at Start Date	0.00834***	41.03
Standard Join Type	0	.
Rejoin Join Type	-0.126***	-14.61
Countdown Join Type	-0.00933	-1.16
Discount Join Type	-0.0540***	-7.40
Referral Join Type	-0.193***	-15.02
Baseline Weight	0.00204***	12.24
Male	-0.00537	-0.44

Predicted Attendance after 12-Weeks	0.468***	10.73
Constant	-4.155***	-121.40
mills		
lambda	-1.525***	-28.28
N	393,318	

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

Appendix 19: Selection Output for the Heckman Correction Model Predicting Weight-Change at 2-Years

Variable	Coefficient	t-statistic
Attendance after 1-Year		
Target Weight Change	-0.0000250	-0.07
Income IMD Quintile	0.0174***	4.57
Diabetic	-0.00556	-0.33
Full Attendances	0.0596***	27.83
Total Attendances	0.109***	15.64
Education and Skills Quintile	-0.00721	-1.90
Age at Start Date	0.00779***	29.07
Standard Join Type	0	.
Rejoin Join Type	-0.133***	-12.51
Countdown Join Type	0.0100	1.14
Discount Join Type	-0.0488***	-5.91
Referral Join Type	-0.0422**	-2.96
Baseline Weight	0.000900***	4.77
Male	-0.0413**	-3.08

Predicted Attendance after 12-Weeks	0.180***	3.65
Predicted Attendance after 6-Months	1.210***	22.54
Constant	-3.538***	-69.69
mills		
lambda	-1.852***	-14.78
N	393,318	

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

Appendix 20: Table 31 with Categorical IMD Variables

Variable	Coefficient (6-Months)	t-statistic (6-Months)	Coefficient (12-Months)	t-statistic (1-Year)	Coefficient (24-Months)	t-statistic (2-Year)
Target Weight Change	0.0108***	15.52	0.0285***	16.31	0.0363***	10.85
Income IMD Quintile 0	0	.	0	.	0	.
Income IMD Quintile 1	-0.0512*	-2.26	-0.00131	-0.02	-0.158	-1.4
Income IMD Quintile 2	-0.0878**	-3.29	-0.0247	-0.36	-0.0762	-0.57
Income IMD Quintile 3	-0.0916**	-3.13	-0.0606	-0.81	-0.169	-1.16
Income IMD Quintile 4	-0.0602	-1.87	-0.0142	-0.17	-0.0479	-0.3
Diabetic	-0.0671*	-1.97	0.225**	2.71	0.204	1.34
Full Attendances	-0.122***	-48.83	-0.0734***	-9.32	-0.0113	-0.6
Education and Skills IMD Quintile 0	0	.	0	.	0	.
Education and Skills IMD Quintile 1	0.0520*	2.34	-0.0105	-0.18	0.0505	0.46
Education and Skills IMD Quintile 2	0.0743**	2.84	0.0835	1.25	0.0131	0.1
Education and Skills IMD Quintile 3	0.0670*	2.32	0.113	1.53	0.133	0.93
Education and Skills IMD Quintile 4	0.0951**	2.96	0.167*	2.03	0.0950	0.6
Age at Start Date	-0.0179***	-40.81	-0.0184***	-16.13	-0.0138***	-5.89
Baseline Weight	-0.00306***	-8.02	-0.0248***	-25.35	-0.0491***	-25.13

Male	0.651***	24.32	1.193***	17.87	1.314***	10.28
LOCF Weight-Change 3 Months	1.419***	664.79	-	-	-	-
Heckman Weight-Change 6 Months	-	-	1.154***	296.67	-	-
Heckman Weight-Change 12 Months	-	-	-	-	0.919***	137.63
Constant	2.847***	62.94	4.838***	31.77	5.727***	14.27
Selection Output						
	Attendance after 12-Weeks		Attendance after 6-Months		Attendance after 1-Year	
Target Weight Change	-0.000145	-0.42	-0.000310	-0.98	-0.0000261	-0.08
Income IMD Quintile 0	0	.	0	.		
Income IMD Quintile 1	0.0315**	2.89	0.0516***	5.11	0	.
Income IMD Quintile 2	0.0572***	4.44	0.0915***	7.69	0.0336**	2.95
Income IMD Quintile 3	0.0849***	6.00	0.112***	8.6	0.0552***	4.1
Income IMD Quintile 4	0.0960***	6.17	0.131***	9.15	0.0678***	4.58
Diabetic	-0.0305	-1.66	-0.0180	-1.15	0.0717***	4.4
Full Attendances	0.0572***	42.51	0.0815***	67.88	-0.00557	-0.33
Total Attendances	0.463***	286.03	0.241***	43.39	0.0596***	27.84
Education and Skills Quintile 0	0	.	0	.	0.109***	15.64
Education and Skills Quintile 1	0.00630	0.59	-0.01570	-1.59	0	.
Education and Skills Quintile 2	0.0239	1.89	-0.00970	-0.83	-0.000550	-0.05
Education and Skills Quintile 3	0.0420**	3	-0.0122	-0.95	-0.0165	-1.26
Education and Skills Quintile 4	0.0482**	3.1	-0.0212	-1.48	-0.0149	-1.03
Age at Start Date	0.00554***	25.4	0.00833***	40.99	-0.0298	-1.85

Standard Join Type	0	.	0	.	0.00778***	29.03
Rejoin Join Type	0.0126	1.48	-0.125***	-14.58	0	.
Countdown Join Type	0.0858***	9.47	-0.00930	-1.16	-0.132***	-12.5
Discount Join Type	-0.0152	-1.89	-0.0536***	-7.35	0.0100	1.14
Referral Join Type	0.0282	1.84	-0.192***	-14.99	-0.0485***	-5.87
Baseline Weight	0.00134***	7.33	0.00204***	12.24	-0.0420**	-2.93
Male	0.0344*	2.49	-0.00555	-0.46	0.000901***	4.78
Predicted Attendance after 12-Weeks	-	-	0.468***	10.73	-0.0415**	-3.1
Predicted Attendance after 6-Months	-	-	-	-	0.180***	3.65
Constant	-4.532***	-204.49	-4.165***	-120.57	1.210***	22.53
mills					-3.552***	-69.57
lambda	-0.590***	-33.23	-1.527***	-28.3		
N	393,318		393,318		-1.855***	-14.79
					393,318	

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

Appendix 21: Table 32 with Categorical IMD Variables

Group	N	LOCF Weight-Change (kg)	Heckman Correction Predicted Weight-Change (kg)
Full Sample	393,318	-4.328 (4.718)	-3.993 (4.756)
Attended after 3 months (observed)	191,275	-6.925 (5.329)	-6.722 (4.755)
Last attendance before 3 months (unobserved)	202,043	-1.870 (2.006)	-1.410 (2.984)

*standard deviation in parentheses

Appendix 22: Table 33 with Categorical IMD Variables

Group	N	LOCF Weight-Change (kg)	Heckman Correction

			Predicted Weight-Change
Full Sample	393,318	-4.532 (5.535)	-3.510 (5.848)
Attended after 6 months (observed)	107,767	-9.454 (7.470)	-8.278 (5.896)
Last attendance between 3 and 6 months (unobserved)	84,187	-4.606 (3.753)	-5.011 (5.181)
Last attendance before 3 months (unobserved)	201,364	-1.867 (2.003)	-0.335 (3.715)

*standard deviation in parentheses

Appendix 23: Table 34 with Categorical IMD Variables

Group	N	LOCF Weight-Change (kg)	Heckman Correction Predicted Weight-Change
Full Sample	393,318	-4.387 (5.522)	-3.0581 (5.914)
Attended After 12 Months (observed)	55,042	-10.644 (8.995)	-8.494 (6.212)
Last attendance between 6 and 12 months (unobserved)	53,523	-7.115 (5.682)	-6.668 (5.812)
Last attendance between 3 and 6 months (unobserved)	83,588	-4.587 (3.744)	-4.443 (5.298)
Last attendance before 3 months (unobserved)	201,165	-1.867 (2.003)	-0.0543 (3.981)

*standard deviation in parentheses

**Last attendance before 3 months was lower when predicting weight-change at 24 months as some participants who dropped out in the first 3-months attended again after a year

Appendix 24: Quality Assessment of Studies Included in the Systematic Review

Dimension	Question for Critical Appraisal	Gray et al. (2018)	Thomas et al. (2017)	Michaud et al. (2017)	Zomer et al. (2017)	Ahern et al. (2017)	Smith et al. (2016)	Haussler and Breyer (2016)	Hoerger et al. (2015)	Wilson et al. (2015)	Fuller et al. (2014)	Lewis et al. (2014)	Meads et al. (2014)	Ginsberg and Rosenberg (2012)	Miners et al. (2012)	Forster et al. (2011)	Cobiac et al. (2010)	Trueman et al. (2010)	Gustafson et al. (2009)	Bemelmans et al. (2008)	Galani et al. (2007)	Roux et al. (2006)	Olsen et al. (2005)
Structure (S1)																							
S1	Is there a clear statement of the decision problem?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Is the objective of the evaluation and model specified and consistent with the stated decision problem?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Is the primary decision maker specified?	Y	Y	U	Y	U	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	Y	Y
S2	Is the perspective of the model stated clearly?	Y	Y	U	Y	U	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	Y	U

	Are the model inputs consistent with the stated perspective?	Y	Y	U	Y	NA	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	Y	Y	U	Y	Y	Y	U
	Has the scope of the model been stated and justified?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	Y	Y	Y	Y	Y	Y	N
	Are the outcomes of the model consistent with the perspective, scope and overall objective of the model?	Y	Y	U	Y	U	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	Y	Y	U	Y	Y	Y	U
S3	Has the evidence regarding the model structure been described?	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	N	Y	N	Y	Y	N	Y	N	Y	Y	Y	Y
	Is the structure of the model consistent with a coherent theory of the health condition under evaluation?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	U	Y	U	Y	Y	U	Y	U	Y	Y	Y	U
	Have any competing theories regarding model structure been considered?	N	Y	U	N	N	N	Y	N	Y	N	N	U	N	Y	Y	N	N	U	N	N	N	N
	Are the sources of data used to develop the	Y	Y	Y	N	Y	N	Y	U	Y	Y	N	N	U	Y	Y	Y	Y	Y	Y	Y	N	Y

	structure of the model specified?																						
	Are the causal relationships described by the model structure justified appropriately?	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	N	Y	N	Y	Y	U	Y	U	Y	Y	Y	N
S4	Are the structural assumptions transparent and justified?	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	N	Y	N	Y	Y	N	Y	N	Y	Y	Y	N
	Are the structural assumptions reasonable given the overall objective, perspective and scope of the model?	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	N	Y	U	Y	Y	U	Y	N	Y	Y	Y	N
S5	Is there a clear definition of the options under evaluation?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Have all feasible and practical options been evaluated?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Is there justification for the exclusion of feasible options?	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
S6	Is the chosen model type appropriate given the decision problem and specified	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	Y	Y	U	Y	N	Y	Y	Y	N

	causal relationships within the model?																						
S7	Is the time horizon of the model sufficient to reflect all important differences between options?	Y	U	Y	N	U	N	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	U
	Is the time horizon of the model, the duration of treatment and the duration of treatment effect described and justified?	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y
	Has a lifetime time horizon been used?	Y	N	Y	N	N	N	N	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	N	U	Y	Y	N
	If not, has a shorter time horizon been justified?	NA	N	NA	Y	N	Y	Y	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Y	N	NA	NA	Y
S8	Do the disease states (state transition model) or the pathways (decision tree model) reflect the underlying biological process of the disease in	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	U	Y	Y	U	Y	U	Y	Y	Y	N

	question and the impact of interventions?																						
S9	Is the cycle length defined and justified in terms of the natural history of disease?	Y	Y	Y	Y	U	Y	Y	U	U	Y	N	Y	N	N	N	N	N	N	N	Y	U	N
Data (D)																							
D1	Are the data identification methods transparent and appropriate given the objectives of the model?	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	U	Y	Y	N
	Where choices have been made between data sources, are these justified appropriately?	U	Y	Y	U	U	N	U	N	U	Y	U	Y	U	Y	Y	Y	N	U	N	U	Y	U
	Has particular attention been paid to identifying data for the important parameters in the model?	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	U	Y	U	Y	Y	Y	Y	U	U	Y	Y	N
	Has the process of selecting key parameters been justified and systematic methods used to	N	Y	N	N	U	N	N	N	Y	N	N	Y	N	N	Y	Y	N	N	N	U	Y	N

	identify the most appropriate data?																						
	Has the quality of the data been assessed appropriately?	N	Y	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	U	U	N
	Where expert opinion has been used, are the methods described and justified?	Y	Y	NA	NA	NA	NA	NA	NA	Y	Y	NA	NA	Y	NA	NA	NA	NA	NA	NA	NA	NA	NA
D2	Are the pre-model data analysis methodology based on justifiable statistical and epidemiological techniques?	Y	Y	Y	NA	Y	Y	Y	U	Y	Y	Y	Y	U	Y	Y	Y	Y	Y	Y	Y	Y	N
D2a	Is the choice of baseline data described and justified?	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	U	Y	Y	Y	Y	Y	Y	Y	Y	N
	Are transition probabilities calculated appropriately?	Y	Y	Y	U	U	Y	Y	U	U	Y	U	Y	U	Y	Y	U	U	U	U	Y	Y	U
	Has a half cycle correction been applied to both cost and outcome?	Y	U	N	Y	U	U	N	U	U	Y	N	U	N	N	U	U	U	U	N	Y	NA	N
	If not, has this omission been justified?	NA	NA	N	NA	NA	NA	N	NA	NA	NA	N	NA	NA	NA	NA	NA	NA	NA	N	NA	NA	N

D2b	If relative treatment effects have been derived from trial data, have they been synthesised using appropriate techniques?	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Y	NA	U	NA	NA	NA	NA	NA	NA
	Have the methods and assumptions used to extrapolate short-term results to final outcomes been documented and justified?	N	Y	Y	N	Y	N	Y	N	N	N	Y	Y	Y	N	N	Y	Y	N	N	N	Y	N
	Have alternative extrapolation assumptions been explored through sensitivity analysis?	N	U	U	N	N	N	N	N	N	N	N	N	Y	N	N	Y	Y	N	N	N	Y	N
	Have assumptions regarding the continuing effect of treatment once treatment is complete been documented and justified?	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	N
	Have alternative assumptions been explored	Y	Y	U	N	N	N	N	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	N

	through sensitivity analysis?																						
D2c	Are the utilities incorporated into the model appropriate?	Y	Y	N	Y	N	Y	N	Y	U	Y	Y	Y	U	Y	Y	N	Y	N	U	Y	Y	N
	Is the source for utility weights referenced?	Y	Y	N	Y	N	Y	N	Y	N	Y	Y	Y	U	Y	Y	N	Y	N	N	Y	Y	N
	Are the methods of derivation for the utility weights justified?	Y	Y	N	N	N	Y	N	Y	N	Y	N	Y	N	N	N	N	Y	N	N	Y	Y	N
D3	Have all data incorporated into the model been described and referenced in sufficient detail?	Y	Y	Y	N	N	Y	N	Y	N	Y	N	Y	N	N	N	N	N	N	N	Y	Y	N
	Has the use of mutually inconsistent data been justified (i.e. are assumptions and choices appropriate)?	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	N	NA	NA	NA	NA	NA	NA	NA	NA	NA	Y	NA
	Is the process of data incorporation transparent?	N	Y	Y	N	N	Y	N	N	N	Y	N	Y	N	N	Y	N	Y	N	N	Y	Y	N
	If data have been incorporated as distributions, has the choice of distribution for	N	Y	Y	NA	NA	Y	NA	NA	NA	N	NA	Y	NA	NA	Y	Y	NA	N	N	N	Y	N

	each parameter been described and justified?																						
	If data have been incorporated as distributions, is it clear that second order uncertainty is reflected?	Y	Y	Y	NA	NA	Y	NA	NA	NA	Y	NA	Y	NA	NA	Y	Y	NA	N	N	Y	Y	N
D4	Have the four principal types of uncertainty been addressed?	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
	If not, has the omission of particular forms of uncertainty been justified?	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N
D4a	Have methodological uncertainties been addressed by running alternative versions of the model with different methodological assumptions?	Y	Y	N	U	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y
D4b	Is there evidence that structural uncertainties have been assessed via sensitivity analysis?	N	N	N	N	N	N	U	N	N	N	N	N	N	Y	N	N	N	N	N	N	Y	N

D4c	Has heterogeneity been dealt with by running the model separately for different sub-groups?	N	Y	Y	Y	N	N	Y	N	Y	N	Y	Y	N	N	Y	N	N	N	N	Y	N	N
D4d	Are the methods of assessment of parameter uncertainty appropriate?	Y	Y	Y	U	N	Y	N	N	N	Y	N	Y	N	N	Y	Y	N	U	N	Y	Y	N
	Has probabilistic sensitivity analysis been done?	Y	Y	Y	N	N	Y	N	N	N	Y	N	Y	N	N	Y	Y	N	Y	N	Y	Y	Y
	If not has this been justified?	NA	NA	NA	N	N	NA	N	N	N	NA	N	NA	N	N	NA	NA	N	NA	N	NA	NA	NA
	If data are incorporated as point estimates, are the ranges used for sensitivity analysis stated clearly and justified?	Y	Y	Y	NA	NA	Y	NA	NA	NA	Y	NA	N	NA	NA	Y	Y	NA	N	NA	N	Y	Y
Consistency (C2)																							
C1	Is there evidence that the mathematical logical of the model has been tested thoroughly before use?	N	U	N	N	U	N	U	U	N	N	N	N	N	U	U	N	N	N	N	N	U	N

C2	Are the conclusions valid given the data presented?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Are any counterintuitive results from the model explained and justified?	NA	NA	NA	NA	NA	NA	NA	NA	Y	NA	NA	NA	NA	Y	Y	NA	NA	NA	NA	NA	NA	NA
	If the model has been calibrated against independent data, have any differences been explained and justified?	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
	Have the results of the model been compared with those of previous models and any differences in results explained?	N	Y	Y	N	N	Y	N	Y	Y	Y	N	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y

Appendix 25: Regression Results from Predicting Weight-Change without VLCD Programmes

Variable	Coefficient	t-statistic
Age	0.283	1.89
Female	0.286	0.22
Start Weight	-0.00293	-0.05
Weight Loss Phase	-0.379	-1.26
Weight Loss Phase Squared	0.0143	1.21
Physical Activity Programme	-2.068*	-2.22
Initial Weight Loss	0.388**	3.05
Maintenance Phase	-0.732	-0.79
Time from Weight-Loss Phase End	0.170***	3.57
Time from Weight-Loss Phase End Squared	-0.00159**	-2.79
Constant	-16.25	-1.26
N	52	

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