WHAT DETERMINES WEIGHT LOSS BEHAVIOUR IN AUSTRALIA? EVIDENCE FROM THE HILDA SURVEY

Christopher Soldi, Vincent Hoang, Clevo Wilson

Department of Economics & Finance, Queensland University of Technology, Brisbane, Australia

ABSTRACT

In light of the increasing prevalence of obesity in Australia, this paper undertakes an empirical investigation, using the Household Income and Labour Dynamics Australia survey (HILDA), to identify factors that influence individuals to undertake a weight loss diet. In fact, this study is one of the first empirical investigations, which examine economic choice models regarding weight loss diet decisions. The empirical investigation finds statistically significant relationships between weight loss dieting status and body weight satisfaction, health conditions (i.e. self-assessed health and a diagnosis of serious illness[1]), time pressure (i.e. amount of spare time), socio-economic factors (i.e. age, income, gender, and being a membership of an association). Endogeneity issues that arise due to different lifestyle preferences are addressed through the use of discrete latent factor modelling. These discrete latent factors are also found to have statistically significant effects on individuals' weight loss behaviour.

KEY WORDS: Weight loss behaviour; diet; HILDA; body weight satisfaction; lifestyle preferences

1. Introduction

Australia has the third largest rate of obesity in the world (Organisation for Economic Co-operation and Development, 2014). In Australian, the number of adults in Australia that are overweight or obese rose from 56.3% in 1995 to 62.8% in 2012 (The Australian Bureau of Statistics, 2012). It is forecasted that less than one third of the Australian population will be at a healthy body weight by 2025 (Walls et al. 2012).

Obesity imposes a large financial burden on the Australian economy. In 2005 it was estimated that overweight and obese adults cost the Australian economy $56.6 billion, with $21 billion in direct health care and non-health care costs, and an additional $35.6 billion through government subsidies (Colagiuri, 2010). However, unlike many other health-related issues, overweight and obesity can be reduced through behavioural change. Therefore the economics of choice can play a vital role within the epidemic as it allows a greater understanding of what factors influence an individual's weight controlling behaviours given their limited resources.

---

1 Serious illnesses include arthritis or osteoporosis, asthma, any type of cancer, chronic bronchitis or emphysema, depression or anxiety, type 1 or 2 diabetes, high blood pressure and heart disease.

2 Other possible techniques for addressing endogeneity include instrumental variable

Previously, Rosin (2012) provided a theoretical economic analysis of an individual's decision process for weight-loss dieting. This framework incorporated the benefits and costs of weight loss with other behavioural traits, such as the effort required to diet, the influence of social norms, present-biased time preferences and a distinction between naiveté and sophistication. The framework proposes that dieting is an increasing function of the individual's initial body weight and a decreasing function of effort and social norms. However, the model did not consider time restraints or that individuals may have differing levels of access to resources that are beneficial for weight loss dieting.

Similarly, Goldfarb et al. (2006) put forward graphical models that analyse differing causes of dieting. They suggested that dieting can be age-associated, disease-provoked, physical-life-events-provoked, style-provoked, innovation-provoked or initiated by smoking cessation. This analysis focuses solely on dieting decisions that are being driven by benefits that are derived from weight loss. The analysis does not explain factors that may disincentivise an individual to diet.

Empirical analyses aiming to identify factors related to weight loss attempts have been undertaken by Getaneh et al. (2013), Bersamin et al. (2009), Bayyari et al. (2013) and Zapka et al. (2009). These studies have identified several factors that have a significant effect on weight loss behaviour including dissatisfaction with body weight, receiving weight loss advice from professionals, age, gender, income the number of previous dieting attempts, BMI, perceived impact of weight on social interaction and a higher level of education. However, these studies have utilised very small selective sample sizes that are not nationally representative and in many cases failed to include relevant variables such as income, levels of spare time and the individual's residential location.

Furthermore, the literature suggests that several behavioural traits might produce systematic deviations from the rational choice framework, leading to a condition of overweightness, such as time preferences (O'Donoghue & Rabin, 1999; Dodd, 2008; Zhang & Rashad, 2008; Smith et al., 2005; Komlos et al., 2004; Borghans & Golsteyn, 2006; Wardle & Steptoe, 2003), health consciousness (Wardle & Steptoe, 2003), locus of control (Strickland, 1978; Wallston & Wallston, 1978; Popova, 2013; Norman et al., 1998; Wardle & Steptoe, 2003) and a reluctance to change dietary habits due to either an addiction to certain ingredients or the individual having food neophobia (Dragone, 2009; Levy, 2002; Dovey et al., 2008). As these characteristics are not observable, variations in weight loss decisions are subject to underlying latent factors. Previous analyses have not taken into account these differences in individuals' lifestyle preferences and therefore preference endogeneity has not been addressed.

The following paper undertakes an empirical analysis of weight loss decisions to identify factors that influence such behaviour and the degree of such influence. First, a conceptual framework is proposed to explain the individual's decision process to undertake weight loss behaviours. Following this, the conceptual framework is applied to a nationally representative dataset of Australia. With the use of a nationally representative dataset, this study overcomes many limitations normally associated with identifying predictors and correlates of weight loss as identified by Stubbs et al. (2011). Preference endogeneity is addressed through the use of latent class modelling.

The paper is structured as follows: Section 2 provides the conceptual decision framework and Section 3 specifies the econometric techniques used to undertake the empirical analysis. Section 4 discusses the dataset that was utilised, the subsample taken from the dataset, and the chosen variables and their construction. Section 5 details the concluding results and provides a discussion of the findings. Section 6 concludes the paper.

2. Methodological Background

The following conceptual framework is based on the standard framework of cost-benefit analysis. A cost-benefit analysis approach is used as weight loss is often determined by an individual's behavioural choice and therefore economists expect weight-changing behaviour to occur when the benefits of that change exceed the cost (Philipson, 2001). As weight loss behaviour imposes both costs and benefits on the individual, the framework provides a decision-making framework where the individual compares the costs and benefits of undertaking a weight loss diet and makes their decision accordingly. The following conceptual framework creates a rational choice model, which is then influenced by differences in lifestyle characteristics. By doing this, the model can capture both the underlying concept of economic rationality and the recent findings from behavioural economics.

In the framework of cost-benefit analysis, such weight loss behaviour is expected to provide potential benefits by improving the individual's health and body image (attractiveness). These benefits reduce the disutility of being overweight. However, this type of behavioural change involves many additional costs including financial, access and time costs. For example, accessing exercise facilities may require a paid gym membership, and conducting exercise can cost time. Individuals with limited resources would therefore be under a constraint to undertake such behavioural change.

It is important to note that individuals have differing lifestyle characteristics, which can have implications for weight loss behaviour decisions. While it is possible for individuals to alter or change their lifestyle, asking them to undertake lifestyle change is very difficult and to some extent it goes beyond the inquiry of economic analysis as it can intervene into the freedom of choice of individuals. On the other hand, it is more useful for analysts to examine variations in decision-making across individuals given differences in their lifestyle; therefore, this study examines the factors that determine weight loss decisions conditioning on the lifestyle and genetic characteristics of individuals. In addition, the study defines each individual as an agent who maximizes utility but faces constraints. It is also considered that maximising utility in the weight loss decision framework is equivalent to minimising the disutility of being overweight. In other words, given their lifestyle (L) characteristics, it is proposed that individuals aim to minimise the disutility experienced from exceeding their ideal weight (DU_w) subject to the financial (F), access (A) and time (T) constraints they face.

$$U\ min\ DU_w\ \ subject\ to\ F, A, T\ given\ \ L \tag{3.2}$$

At some point, an individual's current weight can deviate too far from their subjective ideal weight, where, given their genetic and behavioural characteristics as well as their constraints, a change in behaviour to lose weight would be undertaken to increase their overall utility.

Undertaking weight loss behaviour usually requires either a reduction in caloric intake or an increase in physical activity where a reduction in calorie intake usually occurs either through reducing portion sizes or consuming foods that are less energy dense (Whybrow, Pallister, Gibbs, & Stubbs, 2011). A 'healthy eating' diet has been recognised to consist of foods with low-energy density, such as vegetables and fruit (Whybrow et al., 2011). These foods are more expensive in terms of energy per unit cost and per serving (Whybrow et al., 2011). Therefore, it can be seen that undertaking weight loss behaviours comes at an increased financial cost. Given this, it is expected that individuals with a lower income are less likely to undertake weight loss behaviours, such as a weight loss diet.

Some individual's access to resources required for weight loss differs. Queensland Health and Queensland Treasury (2012) found that the cost of a healthy food basket was significantly different between major cities and remote areas. The cost of a healthy food basket in very remote areas was found to be 26% more expensive than in a major city. Furthermore, individuals who live in rural and remote Australia do not have the same access to health services as individuals who reside in a major city (Morell, Kiem, Millsteed, & Pollice, 2014). Access to resources, such as a gym has also been identified as a motivator for healthful weight management for college students (Greaney et al., 2009). However, not everyone has access to such facilities.

Weight loss behaviour often requires the individual to increase the time they spend on physical exercise and/or meal production, thereby incurring an opportunity cost. Therefore, it is expected that the more spare time available to an individual, the more likely the individual is to diet, as the costs of doing so are less than those who have less available time.

3. Method

This study, through the use of the previously designed framework, employs a discrete choice model to a representative Australian dataset, using a two-stage analytical process. A discrete choice model allows the estimation of the magnitude that each cost and benefit has on the decision to undertake weight loss dieting. The first stage uses latent class modelling to control for latent lifestyle differences. As discussed previously, unobservable lifestyle patterns have been found that differentiate between individuals, which have implications for health-based decisions (Wardle & Steptoe, 2003). More specifically, it is hypothesised that unobservable lifestyle patterns exist and that these patterns may influence weight loss behaviour. These factors cannot be directly observed within the dataset, and, were therefore, considered latent factors.

The latent class model classifies people into different groups based on the observed manifestation of the latent factors. The second stage utilises a binomial logistic regression to examine the determinants of the decision to undertake a weight loss diet.

The regression uses observable factors related to the conceptual framework to explore their associations with weight loss dieting decisions. The discrete latent factors estimated from the first stage are also incorporated to account for differences in lifestyle underpinned by these latent factors.

Given lifestyle is a latent phenomenon; latent class models appear to be a natural choice. Latent class models identify homogenous groups of individuals within a heterogeneous

population in order to explain preference endogeneity[2]. This is done through a model-based clustering approach, which relates the latent variables to the discrete categories of observed manifest indicators through statistical modelling. This results in the latent class model estimating the population's underlying latent structure. Following this estimation, statistical tests, such as the likelihood ratio, chi square or parsimony indices, such as the BIC can be used to empirically identify the optimal number of clusters and discrete latent factors.

Latent class discrete factor models are used as they allow the analysis of more than one latent variable, which traditional latent class cluster models do not allow. Furthermore, unlike traditional cluster approaches, latent variables can be dichotomous or ordered rather than solely nominal (Vermunt & Magidson, 2013). Therefore, given the nature of this analysis, a latent class discrete factor model was considered the most appropriate. Latent class models have also been used within the literature to group individuals by lifestyle preferences (de Vries et al., 2008; Laksa, Pasch, Lust, Story, & Ehlinger, 2009; Walker & Li, 2007).

For this empirical analysis, several models were estimated using an increasing number of discrete latent factors. Following this, a model comparison was undertaken to choose the optimal model where selection was based on BIC. In this study, LATENT GOLD statistical software was used to estimate the latent class models.

4. Data

The Australian representative dataset utilised for this empirical analysis was drawn from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. This longitudinal dataset for the year 2009 is collected for all household members over the age of 15 years through both face-to-face interviews and self-completion questionnaires. I obtained an Individual Deed of Licence for Australian Academic and Government Researchers from the Commonwealth Department of Families, Housing, Community Services and Indigenous Affairs, therefore permitting me to utilise the data set for this thesis.

This first empirical study utilises the ninth wave of the HILDA survey as it contained a major health module that provided key variables that were not available in other waves of the survey. Initially this provided 13,301 observations; however after removing incomplete responses and responses with a zero income, 9,797 observations remained. The data used for this study was extracted through the Stata Add-On package, PanelWhiz[3], which is a program that facilitates data assembly and the replication of results.

4.1 1st Stage – Manifest Indicators for Latent Class Modelling

As discussed earlier, evidence suggests that locus of control, time preferences and health consciousness are likely to be associated with differing lifestyle behaviours (Wardle & Steptoe, 2003). Reedy, Haines and Campbell (2005) also provide evidence that differing health behaviour clusters can respond differently to interventions aiming to increase fruit and vegetable consumption. Contingent on this, obesity risk associated lifestyle behaviours are

2 Other possible techniques for addressing endogeneity include instrumental variable approaches, panel data methods and recursive mixed-process models.

3 PanelWhiz (http://www.PanelWhiz.eu) was written by John P. Haisken-DeNew (john@PanelWhiz.eu). Any data and computational errors in this paper are my own.

used as manifest indicators for unobservable behavioural differences. The manifest indicators used within this analysis represent smoking, binge drinking, fruit consumption, vegetable consumption and physical activity. These behavioural differences are likely, as discussed earlier, to lead to individuals valuing costs and benefits differently when it comes to health based decisions. Furthermore, these lifestyle behaviours have been used for latent class analysis by de Vries et al. (2008).

The manifest indicator for smoking was constructed from responses to the survey question "Do you smoke cigarettes or any other tobacco products?" The survey provided five possible categorical responses, and these were subsequently dichotomised to 0 = Smoker, 79.96% (n=7,834) and 1 = Non-smoker, 20.04% (n=1,963).

The manifest indicator to measure alcohol consumption was based on whether the individual engaged in binge drinking. Binge drinking was classified by the survey as seven or more standard drinks for a male or five or more standard drinks for a female in one sitting. The survey asked respondents to indicate the frequency of such events from a choice of seven categorical responses which were subsequently dichotomised into 0 = binge drinking at least once per week, 12.45% (n=1220) and 1 = binge drinking less than once a week, 87.55% (n=8577).

The survey measured the frequency and quantity of fruit and vegetable consumption. For vegetable intake, the responses were dichotomised into 0 = does not consume vegetables every day, 50.31% (n=4929) and 1 = consumes vegetables every day 49.69% (n=4868). For fruit intake, the responses were dichotomised into 0 = does not consume fruit every day, 54.78% (n=5367) and 1 = consumes fruit every day 50.31% (n=4430)[4].

Adult guidelines suggest that at a minimum three, 30 minute sessions of vigorous exercise or five, 30 minute sessions of moderate exercise should be undertaken per week (Schoenborn & Stommel, 2011). The survey asked "In general, how often do you participate in moderate of intensive physical activity for at least 30 minutes?". The categorical response set for this survey question prevented the differentiation of separate scores for vigorous and moderate exercise sessions. Six categorical response were provided, however the response has been dichotomised to be either 0 = doesn't exercise 3 times per week, 48.78% (n=4779) and 1 = exercises at least 3 times per week, 51.22% (n=5018).

4.2 2nd Stage - Dependent Variable for Logistic Regression

It was assumed that an individual who had undertaken a weight loss diet had valued the benefits of weight loss activity greater than the costs. The survey provides a question that asks the respondent "Are you currently on a diet to lose weight?", with a dichotomous response of yes/no. This variable signals that the individual has valued the benefits of undertaking weight loss greater than the costs associated. This dichotomous variable was therefore appropriate for

4 The calculation of mean scores to determine the average amount of serves per day consumed in order to provide comparisons with medically suggested intake rates was precluded by the use of categorical responses in the survey.

the empirical analysis of the framework[5]. Within the sample, 16.61% (n=1,627) of individuals were currently on a diet.

4.3 2nd Stage - Explanatory Variables for Logistic Regression

The following explanatory variables were selected to best reflect the conceptual framework previously proposed. Data from survey responses are used to encapsulate information of the respondent's body weight satisfaction, health, behavioural differences and biological, time and financial constraints. Additional control variables for age, gender and education are also incorporated to account for individual heterogeneity.

It was hypothesised that the more dissatisfied the individual was with their appearance, the more likely they were to diet. Grogan (2006) suggests that body weight satisfaction represents the individual's concern with appearance. Based on this, bodyweight satisfaction was measured in the present study to encapsulate the incentive to diet, as dieting may provide benefits through improving body appearance.

It was hypothesised that the poorer the participants' self-assessment of health, the more likely they were to undertake weight loss behaviour. Self-perceived health measures and the presence of serious illness were used to measure the respondents health. It was hypothesised that individuals who perceived their health worse were more likely to undertake weight los behaviour. Furthermore, as weight loss is often recommended once an individual has been diagnosed with a serious illness it was expected that an individual with a serious illness was more likely to be undertaking a weight loss diet.

The time constraint was measured using the respondents self perceived levels of free time. As the availability of free time decreases, the higher the opportunity costs of time spent on exercising and preparing meals and it is therefore predicted that when free time increases, the likelihood of undertaking weight loss behaviour increases.

In order to incorporate the financial constraint into the analysis, a measure of self-declared total financial year disposable income was used[6]. The imputed values were then transformed by taking the natural logarithm to mitigate the effects of the sharply skewed distribution of income. It is predicted that than an individual with a higher income has a greater probability of undertaking weight loss dieting. This hypothesis is based on the fact that a wealthier individual would have a greater ability to afford relatively higher priced food.

As identified by Goldfarb et al. (2006), certain life events may increase the incentive to undertake or avoid weight loss behaviour. Notably, a female who is pregnant is not likely to diet as weight concerns are likely to reduce (Davies & Wardle, 1994), therefore the incentive to lose weight is likely to be reduced. Similarly, as put forward by Goldfarb et al. (2006), after a woman has given birth she is likely to undertake dieting to lose the excess weight she may have gained during the pregnancy. To control for these life events, a variable was

---

[5] This variable, however, does not measure whether the individual may be taking a non-diet approach to weight loss.

[6] The variable "Financial year disposable total income ($) Positive values [weighted top-coded]" was used. Observations with an income of zero were removed from the analysis.

constructed to denote if the female respondent was pregnant at the time of the study or had given birth a child within the previous six months.

Suggestions have been made to subsidise individuals' membership to fitness clubs in order to improve the incentive undertake better weight control behaviours (National Preventative Health Taskforce, 2009). To analyse whether having access to such facilities increases the likelihood of the individual undertaking weight loss behaviour, a variable representing whether the respondent was an active member of a sporting, hobby or community-based club or association was included. It was hypothesised that access to such clubs are likely to offer the availability of more services that can facilitate weight loss behaviour, such as community support, exercise equipment or the organisation of physical activity. Therefore, an individual with such access may face fewer costs for undertaking weight loss behaviour than individuals who do not have such access. It was therefore hypothesised that individuals who were an active member of a club or association will be more likely to undertake weight loss dieting.

Access to healthy food and health services differs between locations. The cost of a healthy food basket is likely to increase significantly the more an individual's geographical location is remote (Queensland Health and Queensland Treasury, 2012). Given this additional financial cost, it is hypothesised that an individual who does not reside in a major city is less likely to diet than an individual who does as the individual faces greater costs to undertake weight loss dieting. Furthermore, individuals who live in rural or remote areas of Australia have poorer access to health services (Morell et al., 2014). It is therefore hypothesised that they are less likely to diet as being advised by a medical professional to lose weight has been seen as a significant motivator for weight loss behaviour (Getaneh et al., 2013). To analyse this, a dummy variable was used to determine whether an individual resided in a major city.

As previously identified, there is a positive relationship between socioeconomic status and weight-controlling behaviour has been found in previous studies (Siu et al., 2011; Wardle & Griffith, 2001; Jeffery & French, 1996). Therefore, a control for the participants' education level was used that measured the highest level of education achieved by the individual. Furthermore, the allocative efficiency hypothesis put forward by Grossman (1972) suggests that educated individuals are more likely to make better informed and make rational decisions in regards to their health. Fuchs (1982) also suggests that educated individuals are less likely to have present-biased time preferences and therefore are more likely to have increased investments in their health. Therefore it is hypothesised that the higher the education level the more likely the individual is to undertake weight loss dieting.

The descriptive statistics for the variables used in the regression analysis are provided below in Table 1.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Age	45.0591	17.7603	15	97
Total Financial Year Disposable Income	41,199.48	41,555.22	3	651,287
Female	0.5258	0.4994	0	1
Currently Pregnant	0.0308	0.1729	0	1
Given Birth in Last 6 Months	0.0191	0.1368	0	1

Member of Association/Club	0.3945	0.4888	0	1
Resides in Major City	0.6190	0.4857	0	1
Diagnosed with a Serious Illness	0.4313	0.4953	0	1
Individual's Satisfaction with Body Weight				
Very satisfied	0.1001	0.3002	0	1
Satisfied	0.2819	0.4500	0	1
Neither satisfied nor dissatisfied	0.2341	0.4234	0	1
Dissatisfied	0.3086	0.4619	0	1
Very dissatisfied	0.0753	0.2639	0	1
Individual's Self-Assessment of Health				
Excellent	0.1294	0.3357	0	1
Very good	0.3808	0.4856	0	1
Good	0.3413	0.4742	0	1
Fair	0.1194	0.3243	0	1
Poor	0.0290	0.1678	0	1
Self-Perceived Levels of Free Time				
Almost Always	0.0099	0.0990	0	1
Often	0.5359	0.2252	0	1
Sometimes	0.2263	0.4185	0	1
Rarely	0.4883	0.4999	0	1
Never	0.2219	0.4155	0	1
Highest Education Achieved				
Year 11 and below	0.3061	0.4609	0	1
Year 12	0.1581	0.3649	0	1
Certificate III or IV	0.2042	0.4032	0	1
Advanced Diploma or Diploma	0.0922	0.2893	0	1
Bachelor or Honours	0.1396	0.3466	0	1
Graduate Diploma or Graduate Certificate	0.0582	0.2343	0	1
Postgraduate – Masters or Doctorate	0.0414	0.1993	0	1

5. Results

Amongst the 9,797 survey respondents, 5,622 (57.38%) individuals were classified as having an unhealthy bodyweight. However, only 1,286 (22.87%) of these overweight individuals reported that they were undertaking a weight loss diet.

First, latent class modelling was undertaken to identify distinct homogenous lifestyle groups. Using the BIC to identify the optimal model[7], the two discrete factor model with two levels was chosen. The profile output based on this model specification is outlined in Table 2 below. From this output, for each discrete factor, a healthy and an unhealthy group were determined. For the following logit model analysis, a dummy variable was used to denote whether an individual was more likely to be within the unhealthy group of that particular latent trait[8]. It

[7] The smaller the BIC, the more superior the model fit.

[8] An external locus of control, present-biased time preferences and low health consciousness are considered unhealthy traits. However, as latent class modeling is used, the specific trait is not directly identifiable.

was expected that if the individual was more likely to be in the unhealthy group, given that particular latent factor, they were less likely to undertake weight loss behaviour/dieting.

Table 2. Classification of Lifestyle

	Discrete Factor 1		**Discrete Factor 2**	
	Level 1	**Level 2**	**Level 1**	**Level 2**
	Healthy	*Unhealthy*	*Unhealthy*	*Healthy*
Discrete Factor Level Size	0.7880	0.2120	0.5644	0.4356
Indicators				
Non-Smoker	0.8780	0.5082	0.7453	0.8700
Avoids Binge Drinking	0.9818	0.4803	0.9099	0.8309
Eats Vegetables 7 Days a Week	0.5573	0.2723	0.2935	0.7604
Eats Fruit 7 Days a Week	0.5322	0.1549	0.1931	0.7879
Exercises 3+ Times a Week	0.5137	0.5065	0.4335	0.6142

The classification of the healthy and unhealthy level for each discrete factor was based on a comparative analysis of the probability of meeting the set lifestyle standards. The cluster with a higher probability of being a non-smoker, avoiding binge drinking, eating vegetables seven days a week, eating fruit seven days a week and exercising three or more times a week were considered to manifest healthier behaviours. All indicators were given equal weighting and the level that has the healthiest characteristics for the most indicators was deemed the healthy cluster of the discrete latent factor.

For discrete latent factor 1, level 1 was deemed the healthy cluster as they had a higher probability of meeting the healthier outcome in every indicator. In discrete latent factor 2, level 2 was healthier on all indicators compared to level 1 except avoiding binge drinking and was, therefore, labelled the healthy cluster.

The results of the binomial logistic regression are provided in Table 3. For this estimation the odds ratios were calculated to ease the interpretation of the model's coefficients.

Table 3. Results of Logistic Regression

Currently on a Weight Loss Diet	Odds Ratio	Std. Err.
Individuals Satisfaction with Body Weight		
Very Dissatisfied	43.4794***	11.6031
Dissatisfied	23.5026***	6.0435
Neither Satisfied nor Dissatisfied	6.4139***	1.6860
Satisfied	2.8083***	0.7557
Very Satisfied (Base)	-	-
Individual's Self-Assessed Health		
Poor	1.3611	0.2677
Fair	1.2101	0.1676
Good	1.1575	0.1337
Very Good	1.2185*	0.1359
Excellent (Base)	-	-

Individual's Self-Perceived Levels of Free Time		
Almost Always	1.3624	0.3945
Often	1.2895*	0.1831
Sometimes	1.1948*	0.1113
Rarely	1.1571*	0.0894
Never (Base)	-	-
Diagnosed with Serious Illness	1.1986***	0.0817
Age	0.9856***	0.0022
Log of Total Financial Year Disposable Income	1.0875***	0.0353
Female	1.7940***	0.1207
Currently Pregnant	0.3898***	0.0885
Given Birth in Last 6 Months	1.1672	0.0885
Member of Association/Club	1.2784***	0.0798
Resides in Major City	1.1172*	0.0707
Discrete Factor 1 Level 2	0.7751***	0.0648
Discrete Factor 2 Level 1	0.7583***	0.0476
Education		
Postgraduate – Maters or Doctorate	1.0153	0.1672
Graduate Diploma or Graduate Certificate	0.9733	0.1654
Bachelor or Honours	1.0291	0.1705
Advanced Diploma or Diploma	1.2460	0.2174
Certificate III or IV	0.9479	0.1592
Year 12	1.0248	0.1937
Year 11 and Below (Base)	-	-
Constant	0.0118***	0.0056
Pearson's Chi-squared (x^2) (14)	1612.45***	
Pseudo R^2	0.1830	
Correctly Classified	83.93%	
Observations	9,797	

*** p<0.01, ** p<0.05, * p<0.1

In order to incorporate the benefits of dieting through improving health and appearance, three variables were incorporated in this model, namely, self-assessed measures of health, a dummy variable indicating whether the individual had been diagnosed with a serious illness, and self-declared body weight satisfaction. A poorer self-assessed health status, being diagnosed with a serious illness and a poorer level of body weight satisfaction were associated with an increased chance of the individual currently undertaking weight loss behaviour. All the signs of the coefficients as shown reflected the previous hypothesised relationships but the magnitudes of each effect differed greatly.

An individual who assessed their health status as poor were 36.11% more likely to undertake weight loss behaviour. Furthermore, every status worse than excellent had an odds ratio greater than one. This is consistent with the hypothesis as an individual is likely to see potential health improvements through weight loss dieting, however only classifying your health as very good was deemed statistically significant at the 10% level. All other responses were deemed insignificant.

The effect of being diagnosed with a serious illness was found to be statistically significant at the 1% level, indicating that an individual who was diagnosed with a serious illness was 19.86% more likely to be on a weight loss diet than an individual who had not been diagnosed with a serious illness. This finding supported the theoretical assumption by Goldfarb et al. (2006) who suggested that "disease-provoked" dieting occurs when the individual is diagnosed with a condition that requires weight loss to reduce threats to their personal health. This positive relationship was also congruent with the studies undertaken by Getaneh et al. (2013) and Zapka et al. (2009).

Bodyweight satisfaction was found to be the strongest influencing factor in the model. All dummy variables were significant at the 1% level. In comparison to an individual who was very satisfied with their body weight, a very dissatisfied individual was, *ceteris paribus*, 43.48 times more likely to be undertaking a weight loss diet, a dissatisfied individual was 23.5 times more likely, a neither satisfied nor dissatisfied individual was 6.4 times more likely and a satisfied individual was 2.8 times as likely. Further analysis was also undertaken to

The financial constraint was captured through the logarithm of the individual's total annual disposable income. This relationship was statistically significant at the 1% level. The relationship also reflected the hypothesised effect that an individual with a higher income was more likely to undertake weight loss behaviour. This also supported the effect of the theoretical income constraint put forward by Rosin (2012). This result suggests that a 1% increase in income is associated with a 4.4% (i.e., log (1.0449)) increase in the odds of being on a weight loss diet.

Determining whether the respondents were a member of an association and whether the individual lived in a major city identified having greater access to resources for weight loss dieting. Both variables were estimated to have a positive association with weight loss dieting behaviour, which therefore supported the previous hypotheses. Results showed that an individual who was a member of an association, *ceteris paribus*, was 27.8% more likely to be undertaking weight loss dieting, and was statistically significant at the 1% level. Residing in a major city was statistically significant at the 10% level and was estimated to increase the probability of being on a weight loss diet by 11.72%.

The signs of the coefficients for age, gender and the control variables for life events (pregnancy and post-pregnancy) were all found to be consistent with the hypothesised effects. A one-unit increase in age was estimated to reduce the odds of being on a diet by 1.44%, statistically significant at the 1% level. This suggested that the theory of "age-provoked" dieting put forward by Goldfarb et al. (2006) was offset by the overall decreasing effect of age. However, the result supported the present study's hypothesis that as age increases the genetic constraint increases as their BMR lowers, which therefore increases the costs associated with weight loss dieting. It was also found that females were 1.794 times more likely to be on a diet than males, significant at the 1% level. Being pregnant was also significant at the 1% level with an odds ratio of 0.39 suggesting that it reduced the odds of the individual dieting. Education was not found to be significant and the coefficients supported no clear relationship, which contradicts previously discussed studies that found a positive relationship between socioeconomic status and dieting (Zapka et al., 2009; Siu et al., 2011). However, a statistically significant positive relationship between dieting and residency area

and income was found suggesting that socioeconomic status may impact the decision to undertake weight loss dieting behaviour.

The two discrete latent variables were all found to be statistically significant at the 1% level. All dummy variables were based on clusters of unhealthier lifestyles. The odds ratio of less than one for all discrete factors suggested that behavioural traits associated with unhealthier lifestyles had a negative influence on an individual's decision to diet. This was consistent with the previously stated hypothesis.

3.6 Conclusion

In summary, the findings of the empirical analysis provided strong empirical evidence for the study's conceptual framework as the hypothesised effects of each variable were supported. The results suggested that body weight satisfaction, self-assessed health, being diagnosed with a serious illness, the amount of spare time available, age, income, gender, being pregnant, being a member of an association/club, residing in a major city and lifestyle characteristics influence the decision to undertake a weight loss diet.

References

Adolfsson, B., Andersson, I., Elofsson, S., Rössner, S., & Undén, A. (2005). Locus of control and weight reduction. *Patient Education & Counseling , 56* (1), 55-61.

Bayyari, W. D., Henry, L. J., & Jones, C. (2013). Dieting behaviours, obesity and predictors of dieting among female college students at Palestinian universities. *Eastern Mediterranean Health Journal , 19* (1), 30-36.

Bersamin, A., Hanni, K. D., & Winkleby, M. A. (2009). Predictors of trying to lose weight among overweight and obese Mexican-Americans: a signal detection analysis. *Public Health Nutrition , 12* (1), 64-73.

Borghans, L., & Golsteyn, B. H. (2006). Time discounting and the body mass index Evidence from the Netherlands. *Economics and Human Biology , 4* (1), 39-61.

Colagiuri, S. (2010). The cost of overweight and obesity in Australia. *Medical Journal of Australia , 192* (5), 260.

Davies, K., & Wardle, J. (1994). Body image and dieting in pregnancy. *Journal of Psychosomatic Research , 38* (8), 787-799.

de Vries, H., van't Riet, J., Spigt, M., Metsemakers, J., van den Akker, M., Vermunt, J. K., et al. (2008). Clusters of lifestyle behaviors: Results from the Dutch SMILE study. *Preventive Medicine , 46* (3), 203-208.

Dodd, M. (2008). Obesity and Time-Inconsistent Preferences. *Obesity Research & Clinical Practice , 2* (2), 83-89.

Dovey, T. M., Staples, P. A., Gibson, E. L., & Halford, J. C. (2008). Food neophobia and 'picky/fussy' eating in children: A review. *Appetite* , 181-193.

Dragone, D. (2009). A rational eating model of binges, diets and obesity. *Journal of Health Economics , 28* (4), 799-804.

Ermini, L., & Hendry, D. F. (2008). Log Income vs. Linear Income: An Application of the Encompassing Principle. *Oxford Bulletin of Economics and Statistics , 70* (Supplement 1), 807-827.

Fuchs, V. R. (1982). *Time Preference and Health: An Exploratory Study.* Chicago: University of Chicago Press.

Getaneh, A., Giardina, E. G., & Findley, S. E. (2013). Factors related to weight loss attempt among Dominican immigrants. *Journal of Immigrant and Minority Health , 15* (3), 591-597.

Goldfarb, R. S., Leonard, T. C., & Suranovic, S. (2006). Modeling Alternative Motives for Dieting. *Eastern Economic Journal , 32* (1), 115-131.

Greaney, M. L., Less, F. D., White, A. A., Dayton, S. F., Riebe, D., Blissmer, B., et al. (2009). College Students' Barriers and Enablers for Healthful Weight Management: A Qualitative Study. *Journal of Nutrition Education and Behavior , 41* (4), 281-286.

Grogan, S. (2006). Body Image and Health Contemporary Perspectives. *Journal of Health Psychology , 11* (4), 523-530.

Grossman, M. (1972). On the concept of health capital and demand for health. *Journal of Political Economy , 80* (2), 223-255.

Jeffery, R. W., & French, S. A. (1996). Socioeconomic status and weight control practices among 20- to 45-year-old women. *American Journal of Public Health , 86* (7), 1005-1010.

Komlos, J., Smith, P. K., & Bogin, B. (2004). Obesity and Rate of Time Preference: Is There a Connection? *Journal of Biosocial Science , 36* (2), 209-219.

Laksa, M. N., Pasch, K. E., Lust, K., Story, M., & Ehlinger, E. (2009). Latent Class Analysis of Lifestyle Characteristics and Health Risk Behaviours Among College Youth. *Prevention Science , 10* (4), 376-386.

Levy, A. (2002). Rational eating: can it lead to overweightness or underweightness? *Journal of Health Economics , 21* (5), 887-899.

Morell, A. L., Kiem, S., Millsteed, M. A., & Pollice, A. (2014). Attraction, recruitment and distribution of health professionals in rural and remote Australia: early results of the Rural Health Professionals Program. *Human Resources for Health , 12* (1), 1-6.

National Preventative Health Taskforce. (2009). *Australia: the healthiest country by 2020 National Preventative Health Strategy – the roadmap for action.* Australian Government, Preventative Health Taskforce, Canberra.

Norman, P., Bennett, P., Smith, C., & Murphy, S. (1998). Health locus of control and health behaviour. *Journal of Health Psychology , 3* (2), 171-180.

O'Donoghue, T., & Rabin, M. (1999). Doing It Now or Later. *American Economic Review , 89* (1), 103-124.

Organisation for Economic Co-operation and Development. (2014). *Obesity Update 2014.* Retrieved 6 23, 2014 from http://www.oecd.org/els/health-systems/Obesity-Update-2014.pdf

Philipson, T. J. (2001). The world-wide growth in obesity: an economic research agenda. *Health Economics , 10* (1), 1-7.

Popova, S. (2013). Locus Of Control - Predictor Of Health And Subjective Well – Being. *European Medical, Health and Pharmaceutical Journal , 4*, 47-52.

Queensland Health and Queensland Treasury. (2012). *The 2010 Healthy Food Access Basket (HFAB) Survey.* Brisbane.

Reedy, J., Haines, P. S., & Campbell, M. K. (2005). The influence of health behavior clusters on dietary change. *Preventive Medicine , 41* (1), 268-275.

Rosin, O. (2012). Weight-Loss Dieting Behavior: An Economic Analysis. *Health Economics , 21* (7), 825-838.

Sabounchi, N. S., Rahmandad, H., & Ammerman, A. (2005). Best-fitting prediction equations for basal metabolic rate: informing obesity interventions in diverse populations. *International journal of obesity , 37* (10), 1364-1370.

Schoenborn, C. A., & Stommel, M. (2011). Adherence to the 2008 Adult Physical Activity Guidelines and Mortality Risk. *American Journal of Preventive Medicine , 40* (5), 514-521.

Siu, J., Giskes, K., & Turrell, G. (2011). Socio-economic differences in weight-control behaviours and barriers to weight control. *Public Health Nutrition , 14* (10), 1768-1778.

Smith, P. K., Bogin, B., & Bishai, D. (2005). Are time preference and body mass index associated?: Evidence from the National Longitudinal Survey of Youth. *Economics & Human Biology , 3* (2), 259-270.

StataCorp. (2013). Stata Statistical Software: Release 13. College Station, TX: StataCorp LP.

Strickland, B. R. (1978). Internal-external expectancies and health-related behaviors. *Journal of Consulting and Clinical Psychology , 46* (6), 1192-1211.

Stubbs, J., Whybrow, S., Teixeira, P., Blundell, J., Lawton, C., Westenhoefer, J., et al. (2011). Problems in identifying predictors and correlates of weight loss and maintenance: implications for weight control therapies based on behaviour change. *Obesity Reviews , 12* (9), 688-708.

The Australian Bureau of Statistics. (2012). *Australian health survey: First results, 2011–12. ABS cat. no. 4364.0.55.001.* Canberra: Australian Bureau of Statistics.

Vermunt, J. K., & Magidson, J. (2013). *Technical Guide for Latent GOLD 5.0: Basic, Advanced and Syntax.* Belmont, MA: Statistical Innovations Inc.

Walker, J. L., & Li, J. (2007). Latent Lifestyle Preferences and Household Location Decisions. *JOurnal of Geographical Systems , 9* (1), 77-101.

Walls, H. L., Magliano, D. J., Stevenson, C. E., Backholer, K., Mannan, H. R., Shaw, J. E., et al. (2012). Projected Progression of the Prevelance of Obesity in Australia. *Obesity , 20* (4), 872-878.

Wallston, B. S., & Wallston, K. A. (1978). Locus of control and health: a review of the literature. *Health Education & Behaviour , 6* (1), 107-117.

Wardle, J., & Griffith, J. (2001). Socioeconomic status and weight control practices in British adults. *Journal of Epidemiology & Community Health , 55* (3), 185-190.

Wardle, J., & Steptoe, A. (2003). Socioeconomic differences in attitudes and beliefs about healthy lifestyles. *Journal of Epidemiology and Community Health , 57* (6), 440-443.

Whybrow, S., Pallister, C., Gibbs, M., & Stubbs, R. J. (2011). The financial costs of a healthy eating weight-loss diet. *Proceedings of the Nutrition Society , 70* (OCE4), E170.

Zapka, J., Lemon, S. C., & Rosal, M. C. (2009). Factors Related to Weight Loss Behavior in a Multiracial/Ethnic Workforce. *Ethnicity & disease , 19* (2), 154-160.

Zhang, L., & Rashad, I. (2008). Obesity and Time Preference: The Health Consequences of Discounting the Future. *Journal of Biosocial Science , 40* (1), 97-113.