Intertemporal Discounting as a Risk Factor for Obesity: An Economic Approach

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Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BMI	Body Mass Index
DALY	Disability-Adjusted Life Year
FIML	Full Information Maximum Likelihood
GHK (simulator)	Geweke-Hajivassiliou-Keane (simulator)
HRQoL	Health-Related Quality of Life
MSL	Maximum Simulated Likelihood
MVP	Mutivariate Probit
NVS	Newest Vital Sign
NWAHS	North West Adelaide Health Study
OLS	Ordinary Least Squares
PDR-M	Positive Discount Rate in Monetary Domain
PDR-H	Positive Discount Rate in Health Domain
QALY	Quality-Adjusted Life Year
REALM	Rapid Estimate of Adult Literacy in Medicine
RCT	Randomized Controlled Trial
SAHOS	South Australian Health Omnibus Survey
SES	SocioEconomic Status
TOFHLA	Test Of Functional Health Literacy in Adults
WC	Waist Circumference
WHR	Waist-Hip Ratio

Abstract

Body weight outcomes, although mediated by genetic and biological factors, are determined to a large extent by lifestyle choices such as diet and exercise. These choices involve a trade-off between immediate pleasure, and expected future wellbeing, since a large part of the health costs of weight gain occur in the future. Understanding of the complex issues around weight-related choices has been contributed to through research in various disciplines including psychology, economics and health research. This thesis contributes from an economic perspective, by focusing on the importance of intertemporal choices as an important determinant of body weight.

To analyse the association between body weight and intertemporal choices, it is important to have an appropriate measure of the rate at which individuals discount future payoffs. This thesis compares various methodologies for eliciting discount rates, before developing a set of stated-preference questions to elicit discount rates that were included in the South Australian Health Omnibus Survey 2008. Based on theory and previous empirical findings, it is investigated whether the standard monetary questions, or questions framed in a health context, are more appropriate to use in the analysis of health out-

comes. Evidence is shown of domain independence of the elicited discount rates, and the more standard monetary domain questions are shown to be more useful descriptors of discounting behaviour in the required contexts.

Using the data obtained on individuals' heterogeneous rates of discounting, as well as the health and demographic data contained in the survey, analysis is conducted to determine if intertemporal discounting is an important risk factor for high body weight, after controlling for other demographic risk factors. There is also some investigation of how these relationships might differ across the relative weight distribution, and by BMI category. It is robustly shown that a high rate of intertemporal discounting in the monetary domain is a significant and quantitatively important risk factor for high body weight.

Discounting behaviour may also be associated with smoking behaviour, and this could complicate the estimation of the relationship between discounting and body weight. Analysis is conducted first to show that the expected association between discounting and smoking behaviour is present, and then to understand how this relationship might bias the estimates of the association between discounting and body weight. Evidence is presented that shows that the estimated association between discounting and body weight is moderated by smoking behaviour, and thus the independent association between discounting and body weight may be higher than first estimated.

Many of the estimation procedures used in this thesis abstract from the pathways of diet and exercise as is appropriate. Separate analysis investigates the joint determination of obesity, diet, and exercise, by estimating a Mul-

tivariate Probit system of equations using Maximum Simulated Likelihood. Evidence is shown of the benefits of this approach for the estimated partial effects of diet and exercise on obesity propensity. This analysis also considers the importance of an individual's degree of planning within this system, and finds evidence that the effect of planning operates primarily through diet and exercise choices.

Declaration

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution to Mark Christopher Dodd, and to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

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Mark Christopher Dodd

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Chapter 1

Introduction

Body weight outcomes are affected by health behaviour choices, such as those regarding diet and exercise. Since an individual's body weight is an important determinant of their health, having implications both for mortality and morbidity, there is considerable interest in the underlying determinants of these choices. Traditionally the field of economics has adopted a *laissez-faire* approach to individuals' decisions, with the assumption that individuals will make the best choices for themselves rendering understanding of the decisions unnecessary. However the decisions related to body weight determination are of particular interest due to a variety of market imperfections, including imperfect rationality, information deficits, and externalities, which make an understanding of the decisions important; firstly to assess whether intervention is justified, and secondly to understand how best to intervene to change individuals' behaviour (Dodd 2008).

Many health related choices can usefully be modelled as investment decisions, which has been common practice since the model of health capital was introduced by Grossman (1972). An important aspect of this thinking is the intertemporal nature of health behaviour choices. In particular this is highly relevant to the issue of body weight determination. Healthy diet and exercise choices in the present will have a positive impact on future health, and this is indeed why such choices are usually made. Discounted utility theory, as introduced by Samuelson (1937), models intertemporal choice by supposing a 'discount rate' across time periods that puts a declining value on utility that is further in the future. In general, individuals with higher discount rates will tend to invest less in a variety of contexts, including health.

Methods for estimating individuals' discount rates have been developed, and it is possible to use these to test for evidence of the presence and magnitude of the association between intertemporal discounting and body weight. While several studies, reviewed in Chapter 2, have attempted to undertake this analysis, results have been mixed, and plagued by issues caused by the choice of discount rate measure. This thesis develops understanding of the role of intertemporal discounting in the determination of body weight outcomes and related health behaviour choices, using original methodologies and analysis.

The background to the issues analysed in this thesis are investigated in Chapter 2 in more detail. This involves first an understanding of the basic health issues around body weight and obesity, as well as the arguments for intervention. There are a large number of theoretical models of health in the literature, many based on ideas of health capital. Many of these general models can be applied to analyse the determinants of obesity and body weight. A number of theoretical models specifically describing body weight determination also have been developed. The literature which proposes and discusses these models, as well as related empirical work, is reviewed in Chapter 2. In particular, special attention is given to the role of intertemporal choice and discounting within the theoretical models, as well as within the empirical analyses. There are only a small number of studies which provide empirical analysis of intertemporal discounting and body weight outcomes. These studies are more thoroughly analysed, not only exposing particular deficiencies of the previous work which are improved upon in the subsequent analysis in this thesis, but also recognising the elements of best practice research that are to be emulated where appropriate.

There are a variety of elicitation methods for intertemporal discount rates, coming under the broad categories of revealed preference, stated preference, or indirect proxies. Various methodologies are compared and contrasted in Chapter 3, with the final goal being the construction of a set of questions to use to elicit intertemporal discount rates for use in later chapters. As well as different types of elicitation procedures, there can also be differences between the elicited measures based on other factors such as framing and contextual domain. In particular, while discount rates are most commonly elicited in the monetary domain, there is evidence that discount rates elicited in the health domain may be quite different. Ultimately, based on many considerations including the constraints of the survey in which the questions are placed, the questions chosen to elicit intertemporal discount rates are two closed-choice stated preference questions, with a large number of options. The questions are designed to be congruent in many ways, but one is set in the monetary domain, while the other is in the health domain. The remainder of Chapter 3 reports the results obtained by the inclusion of these questions in a large and population representative health survey (the South Australian Health Omnibus Survey Spring 2008), including analysis of how the elicited values vary with other variables such as demographics. Importantly, the monetary domain variable and the health domain variable are compared, and evidence is presented to answer some important questions about the differences.

Building on the theory established in Chapter 2, and the indicators of intertemporal discounting constructed in Chapter 3, Chapter 4 reports work on the relationship between intertemporal discounting and body weight, using indicator variables for discounting in each of the domains, and using the BMI (Body Mass Index) as the relevant measure of body weight. Various standard econometric techniques are used to assess the associations between the discounting variables and Body Mass Index (BMI), and the associations with the probability of being overweight or obese, while controlling for other relevant risk factors. Not only discounting, but also the other variables used in the multivariate analysis, are likely to have different associations with BMI at different points of the BMI distribution. For example, a higher level of education is expected to be negatively associated with BMI in the obese and overweight ranges, but would be expected to be positively associated in the underweight range. Quantile regression techniques are used to allow the estimated partial effects of the explanatory variables on BMI to vary across the quantiles of the BMI distribution. In terms of analysis of the associations between discounting and body weight outcomes, this is an appropriate methodology and also an innovation. A further issue of investigation in this chapter is the comparison between the use of the monetary domain indicator of discounting, and the health domain indicator, in the context of body weight.

An individual's degree of intertemporal discounting has implications not only for their body weight related choices, but also for other health behaviours. Smoking behaviour is likely influenced by discounting, and is also directly related to body weight through a number of physiological and behavioural pathways. Chapter 5 explores the relationships between body weight, smoking, and intertemporal discounting. Although models of smoking based on Becker and Murphy (1988)'s forward-looking model of rational addiction are currently popular among economists, there are still those who argue for purely myopic models of addiction. For this reason the first section of Chapter 5 tests the relationship between intertemporal discounting and smoking behaviour, and by doing so provides some evidence in favour of forward-looking models of addiction. This analysis helps motivate the latter part of Chapter 5, where the intermingled relationships between body weight, smoking and intertemporal discounting are investigated. In particular it is investigated whether the exclusion of smoking from analysis of the association between discounting and body weight could bias the results, and how including smoking changes the results. Additionally, it may be discounting that is an important variable to include in estimation of smoking behaviour's effect on body weight, and this is also analysed empirically.

The earlier chapters abstract from the health behaviour pathways of body weight determination such as diet and exercise. Chapter 6 jointly examines the health behaviours of diet and exercise, along with the outcome of obesity. Estimating equations for any of these variables separately would likely lead to endogeneity problems, so a Multivariate Probit (MVP) system of equations is jointly estimated for obesity and selected health behaviours, using Maximum Simulated Likelihood. Different to the previous chapters, the dataset for this analysis is the NWAHS (North West Adelaide Health Study), and is restricted to a subsample of Baby Boomers. The MVP system estimates are compared to more naive single equation estimates. The analysis is then extended to incorporate a variable indicating ‘planning’, which although quite distinct from the discounting variables used in previous chapters, is clearly related and an interesting comparison.

Finally, Chapter 7 concludes, providing a summary of the key original contributions of this thesis.

Chapter 2

Background and Related Literature

2.1 Introduction

This chapter motivates the analysis presented in later chapters and reviews a number of strands of literature that are relevant to them. The literature surveyed includes diverse areas such as intertemporal choice, body weight and health behaviour, spanning disciplines including economics, medicine, psychology and epidemiology, since body weight is so importantly a multi-disciplinary research area (Goode and Mavromaras 2008). It is not contended that the literature presented here is a completely comprehensive survey of any of these areas, but rather provides the key foundations in the literature for the original work presented in this thesis. A detailed review of measures of intertemporal discounting is presented in Chapter 3 rather than in this chapter, as it more naturally is discussed in conjunction with the construction of the survey questions there.

As a major focus of this thesis is body weight and obesity, this chapter first reviews some background information about these issues, including definitions, medical information, and prevalence. An important issue often overlooked in literature about body weight issues is why exactly obesity and being overweight should be considered 'problems' in an economic sense. This issue is discussed in conjunction with a review of the related literature as it is considered an important topic to motivate much of this thesis.

Next, theoretical models of health behaviours and outcomes are presented that are most relevant to the issues of body weight and obesity. Building on this basis, models that are more explicitly tied to body weight are reviewed, as well as emprical analyses regarding body weight outcomes. At this point the evidence is discussed around a number of variables that are commonly associated with body weight outcomes, including education, income and age. The discussion of theory as well as empirical evidence of relationships between particular variables and body weight outcomes is important for the model specifications used in later chapters of this thesis.

The remaining sections of this chapter are devoted to the relationship between intertemporal discounting and body weight outcomes. The theoretical predictions are considered, both with regard to models of body weight, and more broadly to models of health that are applicable. The evidence of previous empirical analyses is reviewed, providing motivation for the major original empirical work in this thesis, in Chapters 4 through 6, as well as the original survey question construction and analysis of Chapter 3.

2.2 Body Weight and Obesity

2.2.1 Definitions

The most commonly used measure of relative body weight is the Body Mass Index (BMI). The BMI is defined as follows:

$$\text{BMI} = \frac{\text{weight(kg)}}{[\text{height(m)}]^2}$$

It is an individual's weight in kilograms, divided by the square of their height in metres. Although the BMI is sometimes said to be measured in units of (kg/m^2), it is most often reported as an index number, without units.

Table 2.1: BMI Categories

Category	Definitions
Underweight	BMI < 18.50
Normal range	$18.50 \leq$ BMI < 25.00
Overweight	BMI ≥ 25.00
Obese	BMI ≥ 30.00

The BMI is commonly used to define categories such as 'overweight' and 'obese'. Although there are some variants on these categorizations, the most commonly accepted system to categorise the BMI of adults is that utilized by the World Health Organization (2004), shown in a simplified form in Table 2.1. The 'obese' category can be further refined, but these categories are not presented here as they are not used in the thesis and are not as consistently defined in the literature. Note also that while the term 'overweight' is defined as below, it is also commonly used to mean 'overweight but not obese'. Care will be taken throughout this thesis to make the distinction where it is important, or where it is not clear from the context.

While by far the most commonly used measure of body weight in social science research, the BMI is not necessarily the most useful in terms of clinical importance, and it has been suggested that researchers should move to other measures where possible (Burkhauser and Cawley 2008, Rothman 2008). Other measures include percent body fat, waist circumference (WC), and waist-to-hip ratio (WHR).

The main measure of weight status used throughout this thesis is the BMI, due to its position as the 'standard' in the literature. This enables comparability to other studies, and is more generally interpretable, with the BMI classifications commonly understood by the general public. Stevens, McClain, and Truesdale (2008) suggest that while the other measures are usually superior predictors of health outcomes, the practical considerations may still act in favour of using BMI. The dataset used in Chapter 4 and Chapter 5 also contains measures waist circumference, while the dataset used in Chapter 6 contains both waist circumference and waist-to-hip ratio data. These alternative measures of weight status will be briefly considered in those chapters, but the focus will remain on the analysis using BMI measures.

2.2.2 Problems Associated with Excess Body Weight

Being overweight or obese is a health concern, and is an established risk factor for a large number of conditions such as high blood pressure, diabetes, cancers, cardiovascular disease and gall bladder disease (Must et al. 1999). The primary health concerns are driven by the amount of excess adipose (fatty) tissue, and the position of this tissue (Kopelman 2000). Relative body weight, while being an imperfect proxy for this, is commonly the factor that is researched, for practical reasons previously discussed. Having a higher body weight than the recommended level is known to cause in an increase in mortality risk, as well as health costs in terms of morbidity and quality of life.

A relatively large number of studies have attempted to estimate the number of deaths attributable to being overweight or obese (See for example Allison et al. 1999, Calle et al. 1999, Fontaine et al. 2003, Mokdad et al.

2004, Flegal et al. 2005). Taking a recent example that is estimated on US data, Mokdad et al. (2004) estimate mortality due to being overweight to be 385000 deaths in 2000 in the US. There are many problems with these types of studies, for example reverse causality and confounders. Diseases that may have been caused by being overweight or obese could lead both to increased mortality risk and to weight loss, which is the problem of reverse causality that can bias estimates of the causal effect of weight on mortality (Flanders and Augestad 2008). Many other variables can act as confouding factors, such as smoking status (Garrison et al. 1983, Durazo-Arvizu and Cooper 2008). A recent workshop addressed the problems of estimating the relationship between body weight outcomes and mortality[1]. Although problems exist when trying to estimate the magnitude of the effect, it is of course still well accepted that excess body weight leads to increased mortality risk to some degree.

As well as mortality risk, obesity and its associated co-morbidities contribute to loss of potential quality of life. Health Related Quality of Life (HRQoL) indicators have been developed that measure the utility attached to a particular health state. Many studies have shown that being overweight or obese has a negative impact on HRQoL (see the review of this topic by Kolotkin, Meter, and Williams (2001).) It is also common to combine mortality with quality of life information to create measures such as Quality Adjusted Life Years (QALYs) or Disability Adjusted Life Years (DALYs).

[1]Relevant publications from this workshop include Cooper (2008), Durazo-Arvizu and Cooper (2008), Flanders and Augestad (2008), Levine (2008), and Robins (2008)

These can also be used in Burden of Disease studies, for example Mathers et al. (2001), who find that 4.3% of the disease burden of Australia in 1996 could be attributed to obesity. Cost of Disease studies convert all the relevant costs to a monetary measure; an example by Access Economics (2008) estimated that the total cost of obesity to Australia in 2008 was $8.283 billion, rising to $58.2 billion if wellbeing costs were included. Simulation studies are also common that focus on the cost of disease in terms of health care costs only, such as van Baal et al. (2008). The interpretation and usefulness of these metrics with respect to obesity are however questionnable (Roux and Donaldson 2004).

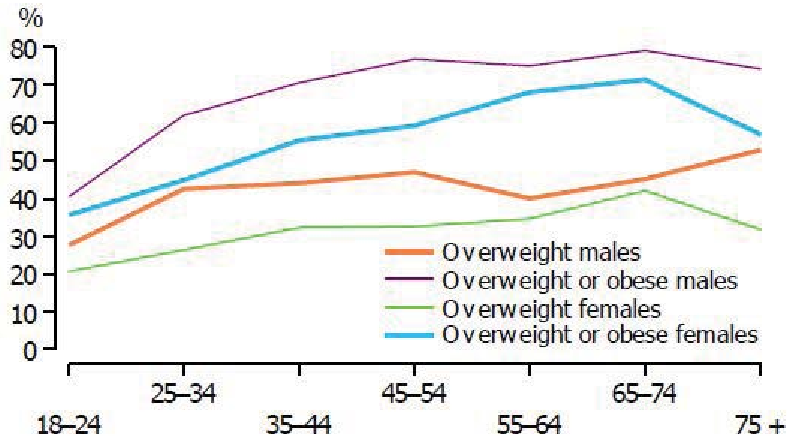
There are also other potential negative effects of being overweight that are not necessarily captured in any of the measures mentioned above. For example, a number of studies purport to have found evidence of a negative effect of obesity on wages, which may be due to discrimination (Baum II and Ford 2004, Cawley 2004b, Garcia and Quintana-Domeque 2007). Weight status can also have effects on self-esteem, and on marriage prospects, but these can vary with social culture (Averett and Korenman 1999).

The above discussion focuses on the impacts of weight in excess of the optimal healthy level, but of course there are problems caused by underweight status also, which are also discussed in many of the papers referenced above. The topic of this thesis focuses primarily on obesity and excess weight, so analysis of underweight status will be relegated to that which is important for understanding the problems of being overweight or obese.

2.2.3 Prevalence of Overweight Status and Obesity

The Australian National Health Survey 2007-2008 (ABS 2009b) found that 25% of adults aged 18 and over were obese, 37% were overweight (but not obese), and only 37% were in the normal weight range. These proportions differ by sex and age as shown in Figure 2.1 (ABS 2009a). There has been a trend towards increasing weight in the Australian population over time. The proportion of men overweight increased from 64% in 1995 to 68% in 2007-08, and the proportion of women overweight increased from 49% to 55% [2].

Figure 2.1: Obesity and Overweight Status by Sex and Age, Australia 2007-2008



Source: ABS Australian Social Trends 2009

The United States similarly has high rates of obesity, with a prevalence in males of 31.3% and a prevalence in females of 33.2% according to data from 2003-04 (Ogden et al. 2006). Not only do many other developed countries have similarly high rates of obesity and overweight individuals, but

[2] This comparison uses figures from the 1995 National Nutrition Survey (ABS 2009b)

even developing countries where a substantial proportion of the population is undernourished have growing problems of overweight and obese individuals (World Health Organization 2004).

2.3 Rationales for Intervention

While there are clearly costs involved with carrying excess body weight, this on its own is no reason to consider obesity a problem that requires government intervention, as is commonly proposed. There would also be less need to understand individuals' choices without the arguments presented below, and discussed in Dodd (2008). The simple economic approach to thinking about obesity, and potential departures from it, have also been discussed by Cawley (2004a) and Mavromaras (2008).

If a consumer makes an informed and rational choice to consume junk food, then attempting to modify this optimizing choice will likely make the consumer worse off. If this individual is attempting to maximize their utility, and they will make the choice to consume only if the benefit they receive from the consumption exceeds the costs, which in the case of junk food should include all future health and financial costs caused by the addition to the waistline. Thus under a model of rational choice in a perfect world, it should be assumed that an individual's exercise and diet choices should be optimal without any intervention. In this scenario, intervention by a third party into the individual's decision process is not only unnecessary, but is also likely to make the individual worse off, since the third party cannot perfectly know the individual's preferences and thus is likely to unintentionally cause deviations from optimal choices.

This hypothetical situation is not necessarily reflective of the real world, but it provides a benchmark from which to assess the relevance of intervention. For there to be an economic rationale for external interventions to be able to increase social welfare, they should attempt to mitigate the damage caused by market failures (the deviations from the 'perfect' scenario). These market failures in the case of obesity can be caused by externalities, information deficits, or imperfect rationality (Dodd 2008). Optimal market outcomes are often based on concepts of efficiency, and only rather weak concepts of equity, so policy makers may also wish to intervene based on their own stronger beliefs regarding the distribution of personal welfare. Particularly since there is evidence that health inequalities related to obesity are closely tied to other socioeconomic factors and inequalities (Hollingsworth and Hauck 2005).

Externalities occur when costs or benefits of a decision are incurred by parties external to the decision. In the case of obesity, the most commonly considered externality is that of a portion of an obese individual's increased health care costs being funded by other taxpayers through public health care. Under this scenario individuals will rationally (implicitly) choose an inefficiently high level of obesity, since they do not consider the full costs of obesity, only the costs that they face personally. External costs can result not just from public health care, but also private health insurance, tax and social security systems, and in many other situations where obese individuals cost more but do not fully pay for this increased cost themselves. Theoretical modeling of the external costs and consequent deadweight loss to society, as well as estimating these costs has been undertaken by a number of researchers (e.g. Keeler et al. 1989, Daviglus et al. 2004, Finkelstein et al. 2004, Bhattacharya and Sood 2007). It should be noted that many of the externalities of obesity are not inherent to the issue, but caused by certain 'imperfections' that have been built into the market. For example, in the case of health insurance, there would be no externality if obese individuals were forced to pay actuarially fair insurance premiums, that would be higher to take into account their expected future costs (Bhattacharya and Sood 2007). It is the regulations that make it impossible to charge different insurance premiums based on measures of obesity (such as community rating) that cause the externality problem in this case.

Information about the consequences of excess weight and obesity, as well as information about the effect of diet and exercise on health are likely to be under-provided in a competitive market. Much of this information is non-rival and non-excludable, making it a 'public good' and therefore under-provided by a competitive market. There is evidence that food-labeling regulation can reduce weight (Variyam 2008), and that health knowledge is related to weight (Kan and Tsai 2004, Nayga 2000). There is also a role for government in ensuring that misleading advertising is minimized, since this can clearly adversely affect choices (Chou, Rashad, and Grossman 2005).

The rational choice model does not propose that individuals make all their decisions by explicitly going through complex maximization processes.

Rather, they will employ heuristics and other decision tools such that they will act optimally, as if they had maximized explicitly. There are potentially many sources of imperfections in rationality that can lead to sub-optimal choices being made. One that could be relevant in the case of obesity is the problem of time-inconsistent preferences, which is not addressed in detail in this thesis, but is discussed in a previous publication (Dodd 2008). Another problem is in the case of children, who may not have the capacity for complex rational decision making, and for example, can be more influenced than adults by persuasive advertising (Chou, Rashad, and Grossman 2005, Smith 2004). There are potentially many other imperfections in rationality, including for example the tendency to eat more when presented with larger portion sizes (Rolls, Morris, and Roe 2002, Just 2006, Wansink and van Ittersum 2003). It may also be considered that unhealthy choices are 'addictive' by certain definitions. Gruber and Köszegi (2001) contrast a model of rational addiction with a model of time-inconsistent preferences and find that they have much in common.

Throughout this thesis the association between intertemporal discount rate and body weight status is analysed. Understanding this is important for two reasons. Firstly, the fact that those individuals with higher discount rates are more likely to be obese is *not* a rationale for intervention, but may be perfectly efficient. Understanding how body weight outcomes depend on this individual trait rather than other issues such as information deficient is important, as it may suggest for example that individuals are 'optimally' overweight and thus it should not be a concern. Secondly, given that there are a large number of rationales for obesity inteventions at the personal and social level as discussed in this section, then a deeper understanding of individuals' decision processes may be useful in targetting behavioural interventions to align with individuals' motivations.

2.4 Economic Models of Health

Before proceeding to discuss economic models of body weight outcomes, it is important to have a basic understanding of the general models of health determination, on which many of the ideas in the specific body weight models are based. Grossman's (1972) seminal paper 'On the Concept of Health Capital and the Demand for Health', while not the first treatment of health as human capital, was the first to present an explicit dynamic model of investment in health capital. A slightly updated treatment is specified in Grossman (2000), the basics of which is presented below due to its importance in the literature.

The key variable in the model is H_t, which is the stock of health at time t. ϕ_t is the service flow per unit stock of health, so that $h_i = \phi_i H_i$ is the consumption of health 'services' in period t. An individual's period utility depends on their consumption of health services h_t, and consumption of another commodity Z_t. The individual maximises an intertemporal utility function that depends on each period, shown in (2.1)

The transition equation for health stock (2.2) shows that health stock depreciates at rate δ_t, but can be added to by health investment I_t. Health investment in turn depends on costly input goods M_t, time TH_t, and human capital such as education E (2.3). Consumption services Z_t are similarly a function of a vector of goods X_t, consumption time T_t, and human captial E (2.4). The mathematical model, with equations specified below also incorporates a budget constraint (2.5), a time constraint (2.6) and a death condition (2.7).

$$U = (\phi_t H_t, Z_t) \quad t = 0, 1, ..., n \tag{2.1}$$

$$H_{t+1} - H_t = I_t - \delta_t H_t \tag{2.2}$$

$$I_t = I_t(M_t, TH_t; E) \tag{2.3}$$

$$Z_t = Z_t(X_t, T_t; E) \tag{2.4}$$

$$\sum_{t=0}^{n} \frac{P_t M_t + Q_t X_t}{(1+r)^t} = \sum_{t=0}^{n} \frac{W_t TW_t}{(1+r)^t} + A_0 \tag{2.5}$$

$$TW_t + TH_t + T_t + TL_t = \Omega \tag{2.6}$$

$$H_t \leq H_{min} \equiv death \tag{2.7}$$

From this model an optimality conditions can be derived for gross investment, which in turn determines the optimal quantities of health capital in each period. Although it is important that the model incorporates both the consumption and investment sides of health, empirical tests of the model have primarily been restricted to the two special cases of the pure investment model and the pure consumption model (Grossman 2000). The pure investment model assumes that healthy time no longer enters the utility funciton directly, whereas the pure consumption model assumes that the cost of health capital is so large relative to its monetary return that the investment motive can be ignored.

Since Grossman's (1972) original article, many theoretical extensions have built upon its basis. The quantity of literature on models of health investment is too large to be adequately reviewed in the scope of this chapter.

Notable extensions have included incorporating insurance (Liljas 1998), focussing on the endogeneity of mortality (Ehrlich and Chuma 1990, Ried 1998, Ehrlich 2000), incorporating behavioural and psychological adaptation to current health state (Gjerde, Grepperud, and Kverndokk 2005), differing formulations that generalise the model (Muurinen 1982), simplifications (Dardanoni 1986, Forster 1989, Eisenring 1999), and complementarities between diseases (Becker 2007).

Other theoretical models of health exist that are based on substantially different frameworks to the standard 'health capital' models. McCarthy (2006) presents a model based on the 'real options' literature. Cutler and Glaeser (2005b) test a simple model based on the correlations of health behaviours. There are of course also a whole slew of models of addiction (e.g. Becker and Murphy 1988, Dockner and Feichtinger 1993, Orphanides and Zervos 1995, Orphanides and Zervos 1998).

2.5 Economic Models of Body Weight Outcomes

Various authors have specified economic models of body weight determination, with the majority of the literature being from around the last decade. Some of these models are simple modifications of more general health or other human capital models, while others are more specifically tailored to the biological aspects of body weight. There is also a difference between models that are employed as frameworks for empirical analyses, and those which are purely theoretical in nature.

Cawley (2004a) for example proposes a simple framework for body weight determination featuring a utility function that includes body weight, a budget constraint, a time constraint, and a transition equation for weight. He does not solve this model, but rather uses it as a simple framework on which to base his discussion of the economic approach to body weight issues. Similarly Goldfarb, Leonard, and Suranovic (2006) use basic economic ideas and diagrams to provide a framework to discuss body weight issues, and explain several phenomena.

Chou, Grossman, and Saffer (2002) provide an analytical framework, which they utilize empirically in Chou, Grossman, and Saffer (2002) and Chou, Grossman, and Saffer (2004). The model itself is not mathematically solved, but rather used as a rationale for a specific reduced form empirical model. In a similar fashion Nayga (2000) does not really propose a new model, but rather a re-labelling of variables in the seminal Grossman (1972) model of health to motivate some reduced form estimations.

Lakdawalla, Philipson, and Bhattacharya (2005) and Lakdawalla and Philipson (2002) use a dynamic model of weight determination to look at the steady-state determinants of weight, and in particular the effects of technological change and income on the equilibrium weight levels. Related empirical work investigates the partial effects of income and exercise, and decomposes the long-run growth in weight into determinants. Philipson and Posner (1999) [and Philipson and Posner (2003)] provides several models of a similar flavour, and also extend the model to endogenize exercise choices, and then allocation of time. A central theme of these four papers, which is also supported by some empirical analysis, is the importance of welfare-enhancing technological change in the recent growth in obesity levels.

Levy (2002) uses optimal control theory to model weight and finds a steady-state weight that is greater than physiologically optimal weight. However, if the individual deviates from the steady state then there will be explosive oscillations in weight. The model is also extended to incorporate social cultural norms. There are a number of models that focus on the importance of individuals' weights with respect to their populations, or to social norms. Etile (2007) considers a model where weight satisfaction depends on social norms, ideal weight and habitual weight. They then empirically test the relationships between social norms, ideal weight, actual weight and food attitudes. Blanchflower, Oswald, and Landeghem (2008) in a working paper derive a model of body weight focusing on the importance of relative weight. The optimization conditions show that if average weight in the population goes up, then a rational individual with concave utility will also increase their weight. Empirical estimation shows that not only own body weight, but also relative body weight are important determinants of body image and also utility. Similar issues are also addressed in Burke and Heiland (2007), who support their model with simulation analysis, and Oswald and Powdthavee (2007), who focus on the fall in life satisfaction caused by affluence, and Dragone (2009), who focuses on habit formation.

Bednarek, Jeitschko, and Pecchenino (2006) model consumption, leisure and health, with behavioural adjustment costs, to determine outcome utility relative to a 'bliss' point. They also argue that the inclusion of adjustment costs adds to the rationale for behavioural intervention, to make sure individuals do not get 'stuck' in a bad position. Based on a similar idea, Suranovic and Goldfarb (2007) run simulations on a boundedly rational model that includes dieting costs (the equivalent to adjustment costs), and use simulations to explain how seemingly inexplicable cyclical dieting patterns can emerge.

Looking at the issue of body weight in a different way to the other models, Smith (2002) uses an economic model to look at the evolutionary history of the problem. He uses an optimal foraging model to explain how the environment of our ancestors could have endogenously generated a utility function and Bayesian priors that are now detrimental to our welfare.

2.6 Empirical Analyses of Body Weight Outcomes

While there are a diverse range of models that look at body weight determination in a variety of different ways, there is often unfortunately little connection between these models and empirical analysis. Since body weight determination is such a complex issue, involving myriad biological, social, cultural and environmental factors, it is very difficult to directly test the models in any strict sense. Often the models are used to generate predictions that are then empirically tested using quite separate econometric frameworks, or the models are linked to reduced form equations that can be estimated. Clearly the estimation of structural models rather than reduced form models is obviously a preference in any analysis, however for the estimation of body weight outcomes current best practice is usually the estimation of an appropriately specified reduced form model. An exception is Rashad (2006), who purports to set out to estimate a structural model of body weight, but in fact the structural equation for body weight still sits on top of a set of reduced form equations for the lifestyle behaviours of caloric intake, exercise and smoking.

The explanatory power of these models tends to be quite low, for example in some studies where R^2 values were reported the values were 4%-8% (Chou, Grossman, and Saffer 2004), 5% (Cutler and Glaeser 2005b), and 11% (Rashad 2006).

The analysis of Chou, Grossman, and Saffer (2004) is based on a reduced form model whereby the body mass outcome (they use both BMI and an indicator for obesity) depends on a vector of personal characteristics including age, ethnicity, income, education, and marital status, and a vector of state-level variables including food prices, cigarette prices and fast-food restaurant density. The main results that stand out are the large positive effect of the number of fast-food restaurants, the evidence of downward trend in food prices as a determinant of body weight increases, and the positive effect of cigarette prices. This article is often cited as evidence of the significance of environment as an important determinant of body weight outcomes, with reference to the restaurant-based variables. However the authors do not account for the potential endogeneity of this variable, which makes their results more open to criticism.

The issue of beliefs about the health risks of being overweight has been examined by several authors. Cutler and Glaeser (2005b), controlling for a vector of demographic variables in a linear probability model for obesity, find that although there is a significant negative relationship between beliefs of the health consequences of obesity and the probability of being obeses, this does not account even for much of the explained variance in obesity. Kan and Tsai (2004) similarly find little significant evidence of health risk knowledge of BMI outcomes, although for the male subsample only they do find a significant positive relationship at lower levels of BMI and a signficant negative relationship at high level of BMI. Nayga (2000) finds health knowledge to be an important determinant of obesity.

It has been suggested that eating can be considered an addictive behaviour, although this is a matter of some contention (Rogers and Smit 2000).

There is also a disconnect between the definition of addiction as a biochemical issue that some would recognise, and definitions based on the effect of current consumption of future utilities and marginal utilities, that is often used by economists. Rational addiction literature refers to food addiction as one of the many applications of the broader theory (Becker and Murphy 1988, Dockner and Feichtinger 1993). However, Dynan (2000) finds no significant evidence of habit formation in food consumption.

Since the paper by Christakis and Fowler (2007), the possibility of social networks being involved in body weight outcomes has recently been a popular hypothesis to test with data in the field of economics. Cohen-Cole and Fletcher (2008) use similar methodologies to the Christakis-Fowler study, while claiming to improve on the method with extra controls, and unlike the original study do not find the expected significant relationships. On the other hand there have been economic papers that find evidence in support of the social networks theory (Trogdon, Nonnemaker, and Pais 2008). In a similar vein are papers that test the hypothesis that relative weight (relative to various nearby subpopulations) may be an important argument of individuals' utility functions, some evidence of this is reported in Blanchflower, Oswald, and Landeghem (2008). Social interactions and self image may also be important factors (Costa-Font and Gil 2004).

Some other interesting studies empirically examine the determinants of body mass outcomes focussing on particular hypothetical determinants such as: GP Supply (Morris and Gravelle 2008), recessions (Ruhm 2000), food stamps (Kaushal 2007), and consuming food as a secondary activity (Bertrand

and Schanzenbach 2009).

2.7 Factors Associated with Body Weight

As mentioned in the previous section, the primary form of the estimations of the determinants of body weight outcomes is a reduced form model of body mass outcome determination. The explanatory variables used in these estimations are guided sometimes by economic theory, sometimes by prior results of association, and sometime by theory or experience from other disciplines. Since at points in this thesis a similar approach to estimation will be taken, this section briefly discusses the theoretical and evidence-based reasons for the inclusion of the main explanatory variables which are commonly used.[3]

2.7.1 Income

There is strong empirical evidence of an independent association between income and body weight outcomes, which is backed up by theoretical models. Most complete models of body weight determination, as well as general models of health investment, incorporate income in some way through a budget constraint. Simpler models treat income as an exogenous variable (Goldfarb, Leonard, and Suranovic 2006), while more complex models allow the endogenous determination of income through labour market and human capital investment choices (Levy 2002, Lakdawalla, Philipson, and

[3]At this point it would be remiss not to mention the important role of family in body weight determination, including factors such as the joint setting of diet, the role of child bearing on a woman's weight, and the effect of parental behaviour on children. These family issues will not be focussed on here, since they are not possible to empirically control for in the cross-sectional analyses presented in the thesis.

Bhattacharya 2005). Within the latter set of models, unearned income is usually treated as exogenous, while earned income depends on other choices. A model designed to describe the impact of price and income changes on body weight is presented by Schroeter, Lusk, and Tyner (2008), they provide an empirical example using price and income elasticities taken from other studies.

Within the empirical literature, income is sometimes considered as a variable of importance on its own, and sometimes it enters the analysis only through variables for Soco-Economic Status (SES). Baum II and Ruhm (2009) empirically analyses how the age-obesity gradient changes by SES, but they do suggest that only small proportion of this acts through income. The association between low SES and many adverse health outcomes, including body weight related issues has been commonly discussed in the literature (James et al. 1997, Burns 2008). In a series of papers, Drewnowski (2004, 2005, 2009) provides evidence of the negative association between obesity and income independently, and analyses the relative cost of calorie dense foods as a major causal factor. Howeveer in certain countries and population subgroups, high income can actually be a risk factor for obesity, for example in Brazil (Monteiro, Conde, and Popkin 2001).

2.7.2 Age

Age is clearly a variable that is relevant for any health outcome. It has been long known that there are direct effects of age on biological functions important to body weight determination such as basal metabolism (Schofield 1985).

People change over time, and therefore age may not only influence biological parameters, but also individuals' preferences, and other time-variant parameters in an economic model. On top of this, since most models of body weight and health capital investment are necessarily dynamic models, the dynamic structure of the model itself will affect the time-profile of body weight outcomes. Age is not usually an explicit variable within economic models of body weight and health, but rather is incorporated into the model by the structure of a dynamic model, and by allowing time variance in certain parameters.

Earlier in this chapter, Figure 2.1 showed the differences in overweight and obesity rates by age and gender from recent Australian statisics. It can clearly be seen that there is generally an upward trend in both the prevalence of being overweight and obese as age increases. However, rather than a linear relationship, it appears almost parabolic, with the change in prevalence decreasing with age, and potentially become negative at the higher ages (Flegal et al. 1998). For this reason, a quadratic term is often included in empirical models to control for the non-linear effect of age. Baum II and Ruhm (2009) shows also that there can be associations between age and the effect of other variables on body weight outcomes, finding a steepening of the SES-obesity gradient for higher age-groups.

2.7.3 Sex

Clearly there are physiological differences between males and females that make the determination of their body weight outcomes fundamentally different. There may also be systematic differences between the preferences of males and females, as well as other elements of their decision processes and environmental constraints.

In general, the prevalence of being overweight is higher among males. This higher prevalence is predominantly caused by a larger prelevance in the 'overweight but not obese' category. According to the Australian National Health Survey 2007-08, 25.6% of males and 24% of females were obese, which is not greatly different. However in the category of 'overweight but not obese' males have a much higher prevalence of 42.1%, compared to females at 30.9% (ABS 2009b).

2.7.4 Education

General education is known to be strongly correlated with positive health outcomes, although there are competing theories about the directions of causality and the pathways of the connection (Grossman 2000). Education was considered an important factor in Grossman's (1972) seminal model of health as human capital, and its importance is also reflected in much of the theoretical literature. In this model education was simply considered as an important exogenous factor determining the efficiency of personal investment.

There is much empirical evidence that education has a negative impact on BMI, the probability of being overweight, and the probability of being obese (Molarius et al. 2000, Nayga 2000, Grabner 2009, Cutler and Lleras-Muney 2010, Webbink, Martin, and Visscher 2010). As well as its direct effects on literacy and knowledge, education can have a strong impact on income and

SES, and thus its effect is often co-mingled with those. Cutler and Lleras-Muney (2010) decompose the effect of education on various health outcomes, including obesity and other body mass outcomes, with their findings varying noticeably depending on the specification.

There are three possible explanations for the observed correlation of education and health outcomes. These are that the direction of causality is from education to health, that it is from health to education, or that it is through a third variable which causes both (or a combination of these). It has often been proposed that a potential 'third variable' is related to intertemporal preference (Grossman 2000).

2.7.5 Health Literacy

Education's effect on body weight outcomes incorporates the impact of education on income, SES, general literacy, and more. It is interesting to look separately at the aspect of literacy directly relevant to health choices, 'health literacy', without confounding it with other aspects of human capital. Health literacy of course may be closely correlated with education and general literacy, but is by nature something distinct. The term health literacy has been defined in varying ways by different authors, and particularly by different disciplines (Nutbeam 2008). The term 'functional health literacy' is also often used to specifically denote not just the individual's health knowledge and ability to comprehend health information, but also their ability to actively operate and make decisions in the health context. In Adams et al. (2009) we find that according to the NVS indicator, 45% of a representative sample of

South Australians have either inadequate functional health literacy, or are at risk of limited functional health literacy.

Nayga (2000) finds a negative relationship between education and BMI (and similarly obesity propensity), but finds that if they also control for individuals' health knowledge, as elicited by some particular diet-disease questions, then the health knowledge variable becomes significant, and the education variable loses its statistical significance. It is inferred from this result that the majority of the effect of education in their original model came from health knowledge. Kan and Tsai (2004) find that a unique measure of health risk knowledge is associated with BMI differently for males and females; for males having a positive effect at lower BMIs and a negative effect at higher BMIs.

One disadvantage of these studies is that the measures they use to quantify health literacy are unique to the studies, and thus cannot be easily compared with other literature. It would be even more useful to have well-validated measures that are reproduced across studies. There are several measures of health literacy that have been developed, including the REALM (Murphy et al. 1993), TOFHLA (Parker et al. 1995), and NVS (Weiss et al. 2005). In the context of body weight there has been little use of these measures to date. Kennen et al. (2005) use the REALM to find significant relationships between health literacy and weight loss knowledge, attitudes and readiness.

2.8 Intertemporal Discounting and Body Weight

2.8.1 Intertemporal Discounting: The Theory

The discussion and study of intertemporal choice has a long history in both economics and psychology, with various positive and normative descriptions proposed (see Frederick, Loewenstein, and O'Donoghue 2002). Samuelson's (1937) seminal paper proposed a general and simple mathematical model for understanding intertemporal choice, which was later dubbed the 'Discounted Utility' model. The idea of this model is that in order to make choices that have an impact on utility over time, an individual will need to make utility over multiple time periods comparable, and this can be done by 'discounting' the value of future utility so that it is worth less than current utility.[4] The reason for future utility to be discounted relative to current utility may be due to a true preference for current utility over future utility, or it may incorporate other factors such as risk of death before future time periods.

The original formulation of this model was expressed in continuous time, but the simplest exposition is the discrete-time version, so that will be briefly discussed here.

An individual receives period utility u_t in each period t from a vector of inputs x_t. For the purpose of exposition, assume the individual lives for a finite T periods, although this can easily be extended to infinite time. At a given point in time, which is denoted $t = 0$, the individual can evaluate the sum of their present and future utility using the following expression, where

[4]The model can incorporate negative discount rates, so that conversely current utility is worth less than future utility, but this is not usually the case.

ρ is the individual's constant discount rate between time periods.

$$U_0(x_0, x_1, ..., x_T) = \sum_0^T (\frac{1}{1+\rho})^k u_k(x_k) \tag{2.8}$$

The discount factor is defined as $\delta = \frac{1}{1+\rho}$, so the above can also be rewritten in terms of the discount factor rather than the discount rate.

$$U_0(x_0, x_1, ..., x_T) = \sum_0^T \delta^k u_k(x_k) \tag{2.9}$$

It is usually assumed that $\delta \in (0, 1)$, or equivalently that $\rho \in (0, +\infty)$, as these assumptions lead to future utility being valued less than current utility.

This original formulated version of discounted utility where the discount rate is a constant is also known as 'exponential discounting'. Since it was proposed, it has been widely used in economics, and is widely used to this day. There are however other models of intertemporal discounting, that operate in a similar fashion, but allow different forms for the discounting function. Commonly proposed alternatives are hyperbolic discounting (Ainslie 1975), and quasi-hyperbolic discounting (Phelps and Pollak 1968, Laibson 1997), which both allow for the discount rate to be a decreasing function of time. In this thesis estimates of discount rates based on the more standard exponential discounting model will be used. Non-exponential discounting in the context of obesity has previously been discussed elsewhere (Dodd 2008).

2.8.2 Intertemporal Discounting and Health

The majority of economic models of health determination are dynamic models, that commonly incorporate an exogenous discount rate for utility (e.g.

Grossman 1972). Since a high discount rate reduces the value of future outcomes, then it will usually lead to less investment in future health, and thus lower health outcomes generally. As a concrete theoretical example, Eisenring (1999) uses comparative dynamics results with a simple model of health investment, to show that a higher discount rate r, will lead to a lower health stock at all times t, and lower health investment in earlier periods $t \in [0, t_1), t_1 > 0$. According to comparative dynamics of Ehrlich and Chuma's (1990) model, a higher discount rate will lead to lower demanded longevity, and generally lower investment in health and health stock.

The first published study to explicitly *empirically* examine the relationship between intertemporal discounting and health behaviour was Fuchs (1982). He uses survey data including six questions about various health behaviours, estimates of discount rates based on choice tasks in the monetary domain, and attitudinal questions. While strong evidence is found of a relationship between intertemporal discounting and schooling, the evidence connecting discounting and the health variables is quite weak, mostly statistically insignificant and with little explanatory power, but generally the relationships at least have the expected direction. While evidence is weak for exercise, dental checkups and weight, the strongest evidence of an effect of intertemporal discounting is found in the estimates for smoking.

Several review articles of discounting in health contexts cover some of the more recent literature (See Cairns 2001, van der Pol and Cairns 2003a, Cairns 2006). While the theory suggests that the discount rate for *utility* should be a factor determining health outcomes, empirical studies usually search for an association between the health outcome of interest, and either a monetary discount rate, or a health-domain discount rate (and sometimes both).

Chapman and Coups (1999) find a small significant association between monetary domain discounting and flu-shot acceptance, but no association between this outcome and health domain discount rate. Results are similarly disappointing in the several experiments discussed in Chapman et al. (2001), with only quantitatively small and rarely significant relationships found between discounting indicators and a variety of preventive health behaviours. These studies along with others are the subject of a meta-analysis in Chapman (2005) which contrasts the general lack of positive results in studies where preventive health is the outcome, with the results obtained in studies looking at addiction, smoking and alcohol consumption. They suggest that the important explanatory power of discounting measures may be derived from the ability to forgo immediate gratification.

Positive associations have been found between illicit drug use and monetary domain discounting (Kirby, Petry, and Bickel 1999, Petry 2003, Bretteville-Jensen 1999), and between illicit drug use and health domain discounting (Petry 2003), and between alcohol and discounting (Vuchinich and Simpson 1998). There have also been many studies which find the predicted associations between discounting and smoking behaviour.[5] This literature is discussed in more detail in Chapter 4.

[5]For example Bickel, Odum, and Madden (1999), Odum, Madden, and Bickel (2002), Baker, Johnson, and Bickel (2003), Ohmura, Takahashi, and Kitamura (2005), Audrain-McGoverna et al. 2009

As well as empirical research attempting to analyse the relationships between discounting and health as its primary focus, discounting has been recognised as a factor relevant in the analysis of other relationships. In particular, it has received some attention as a confounding factor in the estimation of the relationship between health and education. There is debate about whether the correlation between education and health shows the impact of education on health, the impact of health on education, or simply the effect of a 'third variable' on both (Grossman 2008). Intertemporal discount rate is one such potential 'third variable', as higher rates of discounting would be expected to be associated with lower investment in good health, and lower investment in human capital through education. Intertemporal discounting has been mentioned as a strong possibile factor in many analyses of education and health which control for unobservable factors using various econometric techniques, but they do not identify whether or not discounting is in fact one of the unobservables (e.g. Farrell and Fuchs 1982, Berger and Leigh 1989). Cutler and Lleras-Muney (2010) however finds evidence that intertemporal discounting does not account for differences in health behaviour by education.

Some have conversely proposed the possibility of reverse causality in the relationship between discounting and health, whereby a higher level of health (or other human capital) can lead to the development of patience, or a lower discount rate. A theoretical model of this is presented in Becker and Mulligan (1997). Similarly, Orphanides and Zervos (1998) propose a model of addictive behaviour in which addictive consumption and discount rate are both endogenous.

Discounting has also been an important topic of discussion and research with regard to cost-effectiveness analysis, commonly used to evaluate health interventions, since its importance was recognised by Weinstein and Stason (1977).

2.8.3 Intertemporal Discounting and Body Weight Outcomes

There have been a number of studies that have looked at the relationship between intertemporal discounting and body weight outcomes. Many of them are quite preliminary and exploratory in nature, but still provide much interesting evidence on the issue.

Komlos, Smith, and Bogin (2004) test the relationship between intertemporal discounting and obesity using savings and debt as a proxy for intertemporal preferences. They consider the fact that time-series data shows that obesity rates have followed similar trajectories to savings and debt ratios over recent years as evidence of increased discount rates leading to obesity. Also, they examine the correlation between cross-sectional data on countries' net domestic saving rates and obesity rate. The authors do concede that their results are only preliminary empirical evidence of a relationship, since they have not taken account of the myriad of other factors that may have had effects on *both* variables.

Smith, Bogin, and Bishai (2005) regress BMI on whether or not the individual dissaved (their proxy for intertemporal discounting) and a set of control variables. They find some evidence of a positive relationship between these variables as hypothesized, with the evidence stronger for males than females. Zhang and Rashad (2008) investigate the relationship between a subjective binary measure of lack of willpower, and BMI. As expected, a positive relationship is found between these two variables, and similar to the results of Smith et al. the effect is larger for males.

Borghans and Golsteyn (2006) investigate the relationship between BMI and a variety of indicators of intertemporal preferences. Discount rates are estimated using a battery of six choice based questions in the monetary domain, a matching question in regards to number of days in a vacation, and 25 questions relating to intertemporal preferences, including statements of saving behavior, riskiness of investments, planning, and attitude to the future. It should be noted that while the authors have been quite thorough in their selection of indicators of intertemporal preferences, they did not include any indicators explicitly referring to the health domain.[6] Many of the indicators investigated are considered as reasonable proxies for discount rate, and many are related to BMI in the direction expected. Two of the more robust indicators, questions relating to planning and management, are investigated over time. It is found that between 1995 and 2004 the average discount rate did not change significantly, and hence there is no evidence of it driving the growth in BMI. However it is noted that there was a greater increase in BMI amongst those with higher discount rates, which may fit with the theory of Cutler and Glaeser (2005a), that changing relative cost structures, in partic-

[6]The potential domain independence of intertemporal discounting indicators will be discussed in Chapter 3.

ular those caused by technological change, have exacerbated the problem of obesity amongst those lacking in self-control.

While not explicitly addressing obesity or weight issues, Huston and Finke (2003) investigate the role of intertemporal preferences in diet choice, a major proximate cause of weight determination. Based on a theoretical model derived from the (Grossman 1972) model of health capital, diet is assumed to be determined by market factors, sociocultural factors and future discount rate. Their empirical results show that the variables chosen to proxy for intertemporal discount rate were all individually important for diet choice, and together explain the most variation in diet choice out of the three categories of variables. However it should be pointed out that these strong results hinge on the suitability as proxies for intertemporal preference of the variables: education level, smoking status, usage of nutrition labels, exercise, and nutritional knowledge motivation. While it is true that these variables are influenced strongly by intertemporal preference, they are also likely to contain many other factors, perhaps making them poor proxies for intertemporal preference.

In a slightly different vein to the studies of discount rates and intertemporal preference discussed above, the psychological literature has focused more on looking at the relationship between weight and measures of impulsivity, future time perspective, conscientiousness and self-control. Some studies that have found significant positive relationships (not necessarily causal) between impulsivity measures and obesity include: Ryden et al. (2003), Nederkoorn et al. (2006), and Fassino et al. (2002). Nederkoorn et al. (2006a) do not find a significant relationship between self-report measures of impulsivity, including an estimate of discount rate, but do find some evidence with a behavioural stop signal task.

Stutzer (2006) analyzes the relationships between a subjective measure of experienced utility, obesity, and subjective measures of limited willpower. He finds, as expected, that there is evidence of obesity having a negative effect on subjective well-being for those with limited willpower, but not for those with no willpower problems. The implication being that the people without willpower problems who are obese are so because that is the utility maximizing choice for themselves, whereas the obese individuals with willpower problems may be able to be made better off by restricting their obesity-inducing choices.

Scharff (2009) discusses the potential relationship between hyperbolic discounting and obesity, and supports this with empirical analysis. The analysis incorporates variables related to dieting and self-control, that would be important if the individual was time-inconsistent as suggested by hyperbolic discounting, but does not directly elict discounting measures. On the other hand, a recent paper by Ikeda, Kang, and Ohtake (2010) directly estimates discount rates, and finds evidence that magnitude of discount rates, whether they are a hyperbolic discounter, and whether they show evidence of 'sign effect', all have the expected positive effect on the probability of being obese.

Many of the papers mentioned above proxy for intertemporal discounting using variables that would not partial out the effect of discounting from other factors. In Chapters 4 and 5 of this thesis stated-preference indicators of intertemporal discounting are used, which although imperfect, are more likely to show the separate effects of discounting. These variables are discussed in detail in Chapter 3. Borghans and Golsteyn (2006) and Ikeda, Kang, and Ohtake (2010) have used similar variables in their analyses, so their results will be the most suitable comparison to the results from later in the thesis.

Considering the strong theoretical basis for an effect of intertemporal discount rates on body weight outcomes, it is surprising that some of the previous papers on the topic have not found the expected associations, or found associations of a small magnitude. None of the previous empirical analyses have used stated-preference measures of discounting in the *health* domain, which will be done in this thesis. This thesis will also improve the analysis by considering the potential for there to be different effects of discounting on BMI across the BMI distribution, and by considering the effect of smoking behaviour on the relationship. These contributions may also help to explain why some of the results previously found have not been as expected. The specific original contributions of this thesis in relation to the literature are discussed in more detail in Chapter 4 and Chapter 5 where the analysis is presented. To explore some of the many questions still unanswered in this literature, it is necessary to have good measures of intertemporal discounting in both the monetary and health domains. These variables will be developed in Chapter 3.

2.9 Conclusion

This chapter has discussed the relevant background to the issues of body weight and obesity required to support the analysis of the rest of the chapters. In particular it has motivated why it is important to understand the determinants of individuals' choices that are involved in body weight determination, and has suggested that one such major determinant may be individuals' heterogeneous rates of intertemporal discounting. After reviewing other studies that have attempted to analyse the relationship between intertemporal discounting and body weight, it was found that many of the studies are lacking due to their use of discounting measures that are highly likely to be representing other factors. Also, many of the studies have found difficulties showing this relationship, which theory says should be present, and one could argue would likely by strong. The remainder of this thesis in Chapters 4 through 6 explores some particular ideas that may explain why the results to date have been lacking. But first, Chapter 3 turns to the discussion of eliciting measures of intertemporal discounting, the construction of appropriate survey questions that were inserted into a broader health survey, and the analysis of these measures.

Chapter 3

Construction and Analysis of Stated-Preference Indicators of Intertemporal Discounting

3.1 Introduction

The previous chapter motivated the analysis of intertemporal discounting and body weight outcomes that is the focus of this thesis. To empirically analyse these issues, it is important to have good measures of intertemporal discounting. Unfortunately, an individual's discount rate is a difficult parameter to accurately measure. This chapter gives an introduction to the elicitation procedures for these types of variables, including considering particular issues of eliciting discount rates in the health domain. Based on this background, stated-preference questions are developed which were used in the South Australian Health Omnibus Survey (SAHOS), providing one of the main data sources for other chapters of this thesis. The rationales behind the specific construction of these questions are discussed, which ultimately give rise to two variables: an estimate of the discount rate in the monetary domain, and an estimate of the discount rate in the health domain. It is found that a large number of the survey respondents did not show evidence of a positive discount rate in each of the domains. The variation in discounting behaviour cannot be explained well by demographic variables, which is a good indication that the measures captured are of distinct constructs, which it is hoped accurately reflect true discounting behaviour. It is also found, similar to previous studies, that discounting behaviour in the monetary domain is not strongly correlated with discounting behaviour in the health domain.

3.2 Eliciting Intertemporal Discounting Measures

3.2.1 Elicitation Procedures

This section discusses the elicitation of discount rates and intertemporal discounting measures in general. The discount rate of Samuelson's (1937) discounted utility model is a discount rate for *utility*. However the majority of studies in this area use trade-offs in terms of money to estimate *monetary* discount rates. Under the assumption of (approximate) linearity of utility in money for small amounts, these monetary discount rates are often re-interpreted as proxies for or indicators of utility discount rates. Methods of elicitation of discount rates can generally be divided into two types using van der Pol and Cairns (2003b)'s taxonomy: revealed preference and stated preference methods.

Revealed preference methods derive measures of intertemporal discounting, including estimates of discount rates, using field data of natural experiments. The researcher finds data regarding naturally occurring choices, that provide information regarding the implicit discount rates that were used in making the decision. Examples include analysing the wage-risk trade-offs (Viscusi and Moore 1989, Moore and Viscusi 1990), the choice of the quality of consumer durables (Hausman 1979), life-cycle saving behaviour (Carroll and Samwick 1997), and human capital investment decisions (Lang and Ruud 1986).

Stated preference methods estimate measures of intertemporal discounting through data obtained from the responses to hypothetical questions in experimental and survey contexts. However when financial incentives are put in place in an experimental context, the line between stated and revealed preference methods may be blurred somewhat. However this thesis will continue to refer to all studies based on experimental and survey questions as 'stated preference' methods, following the terminology of van der Pol and Cairns (2003b), since they are not revealing behaviour in an authentic behavioural context. Within the stated preference methods, questions can usually be further refined into the categories of open-ended questions, closed-ended choices, pricing/rating tasks and hypothetical scenarios. There are of course many questions within studies that cannot be so neatly characterized, so this is simply an example of the commonly used types of questions.

Open-ended ended questions, also often called matching tasks, involve the subject stating a particular value in the variable Option B, which makes it indifferent to the constant Option A. For example:

> *Option A: You receive \$100 today.*
> *Option B: You receive \$$x$ in one year.*
> *State the value of x at which you are indifferent between the two options*

Since these type of questions are often difficult for the subject to understand, they are sometimes presented with a visual aid suggesting possible responses, this is known as the payment card technique.

Closed-ended choice questions, often also just called choice tasks or discrete choice tasks, involve making a choice between two temporal prospects.

For example:

> *Option A: You receive \$100 today.*
> *Option B: You receive \$110 in one year.*
> *Please select the option you prefer from the above two options.*

The above example is of a single discrete choice. Some studies follow-up the first question with further discrete choice questions, which are selected after the initial choice/s to more accurately estimate the value at which the individual becomes indifferent. Another variant of a discrete choice experiment is to ask a series of discrete choice questions that is set at the outset of the experiment. These latter methodologies are sometimes also known as Multiple Price List format questions, particularly if their presentation format is of a certain form. Authors that have popularized this format in eliciting discount rates include Coller and Williams (1999) and Harrison, Lau, and Williams (2002).

Pricing and rating methods are methods in which subjects are asked to give a value to a certain prospect on a particular distinct metric. An example of a rating task is:

> *Rate the following scenarios on a scale from 1 to 10:*
> *Scenario 1: You experience constant headaches weekly for twelve months, starting now.*
> *Scenario 2: You experience constant headaches weekly for twelve month, starting in one year.*

A pricing task is similar, but instead of asking for scenarios to be ranked on a certain scale, the subject is asked how much they would pay to avert (or receive) the scenario.

Another broad type of question is a response to a well-described scenario, or simply value judgements or subjective opinions. These could include questions such as: "if you received ten vouchers for a free meal that could be used within 2 years, how many would you plan to use in the first year? How many do you think you would actually use? Would you voluntarily constrain your allocation?" (paraphrased from Ameriks et al. 2007). Questions could also include things such as "Do you often put off doing chores?", or "Do you consider yourself to be patient?".

3.2.2 Potential Biases and Confounds

Unfortunately, there are myriad of factors that complicate the elicitation of intertemporal discounting measures using any of the preceding methodologies. Here some of those confounding factors are briefly examined, in particular focussing on perhaps the most common set of methodologies using monetary choices to estimate discount rates in experiments or surveys.

A major problem is that of rescheduling of consumption outside the experimental setting. Many studies ignore this issue, implicitly assuming that consumption at each time is equal to income. On the other hand, various authors have suggested that many experimental techniques to elicit discount rates are redundant, since a rational agent will simply maximize total wealth, and reschedule their consumption as they see fit (Cubitt and Read 2007). Coller and Williams (1999) were some of the first authors to investigate the fact that experimentally elicited discount rates may be censored by field opportunities, and take a somewhat intermediate view. If a subject believes that they can earn an interest rate of 10% p.a. outside the lab, then they should prefer to receive \$100 now rather than less than \$110 in one year, since they could do better with their outside opportunities. Thus even if a subject's intrinsic discount rate for utility or consumption was less than 10%, in the lab their revealed discount rate will be censored to a range between the rates they believe they can borrow and lend at outside the lab. Experiments by Coller and Williams (1999) support this hypothesis by providing information to encourage comparison with outside opportunities, however these results could be exaggerated by anchoring and framing effects. A more recent theoretical paper on this topic by Cubitt and Read (2007) supports the views of Coller and Williams, but asserts that a censored data approach to dealing with the issue is insufficient, since there may still be rescheduling occurring in the case where the elicited discount rate is in the interior of the censored range.

Often researchers are more interested in subjects' discount rates over utility or consumption, but are simply eliciting discount rates with respect to money for practical reasons. Thus another potential problem is that the discount rate with respect to money will not be equal to the discount rate with respect to utility unless the utility function is linear in money. This problem is often dealt with by making the assumption that utility is approximately linear in money for the small amounts usually used in experimental settings. However, Chapman (1996b) finds evidence of differences in discount rates between money and utility.

The expectation of changing circumstances can also bias estimates of discount rates. If utility is concave in consumption, then the expectation that you will be richer 5 years from now would reduce the value to you in 5 years of $100. Thus you would need to be given more than $100 in 5 years to compensate you for not receiving $100 now, even if you had a discount rate of zero. This effect will bias estimates of discount rates upwards for those who expect their wealth to increase over the period in question. Similarly, (positive) inflationary expectations will reduce the value to the subject of $1 in the future, and thus upwardly bias the estimated discount rate (Ostaszewski, Green, and Myerson 1998).

Subjective beliefs regarding uncertainty, and therefore risk preferences, are also tied to intertemporal discounting. It may be difficult to tell whether the discounting of future consumption is due to 'pure' intertemporal preference, or to the reduction in the subjective belief that the delayed outcome will be received, for example due to some probability of death of the subject before the later date is reached. Anderson, Butcher, and Levine (2002) discuss the theory of the relationship between time and risk preferences, investigate it empirically, and ultimately recommend jointly eliciting these variables as best practice. However, depending on the context for the usage of the elicited discount rate, this may not be necessary. In the context of investigating individuals' health-affecting decisions, it is in fact the 'messy' rate of intertemporal discounting that is likely to be most relevant, rather than a 'pure' rate.

The often found empirical regularities such as the magnitude effect, the sign effect and the delay effect (which is related to time inconsistency) will be discussed further in the next subsection. Needless to say, biases are likely to result if these effects hold and estimated discount rates are taken out of context. So if a discount rate is estimated using small amounts, and if there is a magnitude effect, then it may not be appropriate to directly apply this discount rate to larger amounts. In particular, if individuals exhibit time inconsistency, then estimating their discount rates based on exponential discounting may produce fallacious results.

A commonly discussed issue with stated-preference techniques is the potential for choices not to reflect true preferences, since there are not strong enough incentives for subjects to correctly reveal their preferences. Coller and Williams (1999) find that discount rates were statistically significantly higher for hypothetical payments than for real payments, whereas Kirby and Marakovic (1995) find that using hypothetical payment lowers discount rates.

Anchoring and framing effects can both also bias the results. Particularly in cases such as closed-ended questions, where the question itself contains a particular implicit discount rate, there would clearly be the potential for the subject to be biased towards whatever anchors are initially presented. How a question is framed can also impact the results as subjects are susceptible to a framing bias; some theories even suggest that how a question is framed can lead to different heuristic techniques being used to solve the problem. Also related to framing, the question may be structured in a way that is confusing or unnatural for the subject, and hence they may be answering a different question to the one that was asked of them. Furthermore, the subject may even *intentionally* answer the question incorrectly, if they have a certain message they wish to portray to the researcher, or if they try to second-guess the purpose of the experiment.

3.2.3 Properties of Experimentally Elicited Discount Rates

The experimental work that has been undertaken to investigate elicited discount rates has found several empirical regularities. Three of the most important, which seem to be quite robust, are the magnitude effect, the sign effect and the delay effect. These can be partially explained by some of the confounds discussed previously. These effects may also be taken as evidence against certain theoretical models of discounted utility maximisation, but that will not be address in great detail here since models of discounting are generally not intended to be normative models, and what is more important for this thesis is the empirical regularities rather than their causes.

The magnitude effect is the commonly observed finding that small amounts are discounted at a higher rate than larger amounts. (Thaler 1981, Kirby 1997, Green, Myerson, and Mcfadden 1997, Chapman and Winquist 1998, Frederick, Loewenstein, and O'Donoghue 2002). Clearly, if what is being directly measured is discount rates with respect to money (or consumption), and utility is non-linear in money (or consumption), then it is possible that there is no true magnitude effect for discounting of utility, the observed effect being simply an artefact of measuring discounting with respect to the intermediate variable. However the effect has been found to be robust even when taking into account such explanations.

The sign effect is the commonly observed finding that gains are discounted more than losses; similarly, negative and zero discount rates also tend to be more common for losses than gains. Evidence of this effect can be found for example in Thaler (1981), and other papers referenced in the reviews of Loewenstein and Prelec (1992) and Frederick, Loewenstein, and O'Donoghue (2002). Shelley (1993) suggests that this effect is connected with other framing issues.

The most concerning of these commonly observed regularities perhaps is the delay effect, which is that discount rates seem to decline with respect to time. In other words, a one-day period today is discounted at a higher rate than a one-day period a year in the future. Evidence of this has been found in numerous studies, including for example Thaler (1981), Myerson and Green (1995), and Kirby (1997). What is concerning about this effect is that it shows evidence against the often used assumption of exponential discounting, where preferences are dynamically consistent. If intertemporal preferences do not conform to the theoretical model of exponential discounting, then they may be dynamically inconsistent (also often called 'time-inconsistent'). In other words, a decision that is made now over temporally distinct prospects may no longer be optimal from the perspective of the same individual at a future time. Issues such as self-control, individuals' understanding of their own changing preferences, and their ability and desire to constrain their future behaviours then becomes relevant. This possibility has given rise to a large theoretical literature that use non-exponential discounting such as hyperbolic discounting (e.g. Laibson 1997, Harris and Laibson 2001, O'Donoghue and Rabin 2001).

3.2.4 Comparison and Evaluation of Procedures

An important question regarding the use of the previously discussed methods to elicit indicators of intertemporal discounting in experimental and survey settings, is 'which one should be used?'. The choice of which format to use should be based on the desire to achieve a measure that has a strong theoretical basis, that is not too cognitively difficult, that is free from biases, that is statistically efficient, has low implementation costs, has high construct validity and internal consistency, and probably many other characteristics. Of course, like most decisions, there are trade-offs. For example a more complex question may provide a measure that has higher construct validity and statistical efficiency, but that is more costly to implement and has a higher risk of some biases due to cognitive difficulty. Furthermore the weight that a researcher should put on the various criteria is likely to differ with the specific research question being addressed and context of the questions. Thus unfortunately, while there certainly may be some dominant views on this issue expressed in the literature, there is not one single best practice elicitation procedure that can be agreed upon for all contexts.

Before addressing the issue of the relative merits and weaknesses of various procedures, there is another important question. Are the measures equivalent? Clearly if they produce the same results, then the selection of methodology can simply be based on the preference of the researcher. There is evidence that the different elicitation methods produce different results. Cairns and van der Pol (2000) find that average discount rates estimated for open-ended choices tend to be higher compared to discrete choice experiments, this result is statistically significant for some of their subsamples, and there is statistically significant evidence that values are not independent of elicitation method.

This subsection focuses primarily on the comparison between the three main methodologies of stated-preference that can be used to elicit a discount rate, that is open-ended choices, closed-ended choices and pricing/rating tasks. Revealed preference estimates from field data such as those that attempt to estimate a discount rate from wage-safety trade-offs are ignored here since they are not a candidate methodology for surveys or experiments, and also because these methodologies suffer from large problems of omitted variable bias. Other methodologies such as scenario responses, value judgements, and so on, are also not discussed in this section, simply because there are an infinite number of variations of these that are quite different, and thus it is difficult to discuss them comparatively as a class. The following discussion of the three relevant methodologies mirrors somewhat the analysis of van der Pol and Cairns (2003b).

The main advantage of open-ended questions is their statistical efficiency and ability to obtain point estimates, while their main weakness is the cognitive difficulty that subjects may have answering them authentically. Unlike the other methodologies discussed here, a single open-ended question can allow the estimation of a point-estimate of a discount rate. This means that a large amount of variation in individual discount rates can be easily captured and provide a rich source of data from which small changes in discount rates can be related to other variables. However, there is some concern that open-ended questions which ask the subject to provide a precise value for something can be cognitively demanding, and can be easily misinterpreted or misunderstood by people who are not used to making those sorts of valuations, particularly in unfamiliar contexts, and who may not have sufficient incentives to use their mental resources. Mechanisms such as incentive-inducing payments can help provide subjects incentives to think carefully about these difficult questions and should lead to more accurate estimates. Another advantage of using open-ended choices is that since a point estimate of discount rate can be obtained with a single question, this can potentially help to lower implementation costs of the study.

The good news about closed-ended choice methodologies is that they are easier and more natural for subjects to answer, however the downside is that they only allow for interval estimates of discount rates, and many questions need to be asked to obtain an estimate of an interval of small size; also there is perhaps a greater risk of framing effects. The result of a single discrete choice question only tells the researcher whether the subjects implicit discount rate is above or below the one implicit in the question. For this reason, when this methodology is used it is common to use a Multiple Price List (MPL) format, where a specified set of questions are asked, or a set of questions that can even be conditional on previous responses, so that the process moves iteratively towards a point estimate. Another downside of the need for more questions is of course the increased costs of implementation. For closed-ended question procedures such as Discrete Choice Experiments (DCE) and Multiple Price List (MPL) format questions, there is always a concern that the subjects will be influenced unduly by the options presented to them. In an MPL question, there may be a tendency for subjects to choose options ‘in the middle’, or be biased in some direction by the belief that the lowest and highest options presented to them are ‘appropriate’ lower and upper bounds. However, Andersen et al. (2006) find no statistically significant difference in the discount rates elicited from intentionally skewed MPL questions, although they do find this framing bias when eliciting a risk aversion measure, and warn that the potential for bias should always be considered. Closed-ended questions are generally easier to answer since they can more closely reflect the types of decisions made in the real world, and there is evidence that this is the case (Tversky, Sattath, and Slovic 1988, Cairns and van der Pol 2000).

Rating and pricing procedures can be designed to elicit point estimates of discount rates, like open-ended questions. The main problem with these methodologies is that that individuals must convert the prospects onto a particular scale that differs from the units of the original allocations of interest. The problem with this is that individuals are likely to have differing maps between the variable of interest and the scale variable. Thus it is difficult to tell how much of the variance of elicited intertemporal discounting variables is due to intertemporal preferences and how much is actually due to differences in this mapping. These questions are most useful in contexts where it is desirable to convert the decisions of subjects into a particular metric such as money. In terms of cognitive difficulty and implementation costs, these questions are likely to sit somewhere between the open- and closed-ended questions.

A final concern is that in the real world where agents are not necessarily the rational beings of economic theory, people may use simple heuristics to make choices. Therefore the type of question used to elicit time preferences itself, as well as framing of the question, can lead people to apply different decision techniques. Thus the differing results of the various elicitation methodologies may reflect the differing heuristics that are naturally applied to each methodology (Tversky, Sattath, and Slovic 1988, Cairns, van der Pol, and Lloyd 2002).

Of course these different data collection methods need not be compared to one another in an effort to find the best measure, but rather can be used as complements to one another. For example Borghans and Golsteyn (2006) use closed-ended monetary trade-off questions, in conjunction with other hypothetical scenario type questions to obtain a large set of differing variables regarding discounting behaviour.

3.3 Are Discount Rates for Health Different?

3.3.1 Eliciting Discount Rates for Health

The number of studies that have incorporated elicitation of intertemporal discounting measures for health is now numerous. Several reviews of the topic and the related literature have also been published in recent times

(Cairns 2001, Cairns 2006, van der Pol and Cairns 2003b, Asenso-Boadi, Peters, and Coast 2008). The methodologies used in the health domain mirror closely those used in other domains, so there is no need to restate these methodologies here. However there are particular aspects of working in the health domain that deserve attention.

When questions are asked about money, the baseline is generally assumed to be the subjects current (and expected) financial states, unless otherwise specified. However the issue of baseline is more complex in health related questions. It may be unclear whether the baseline is 'full health' or 'currently expected health' for example. There can be confusion about how much of personal circumstances to carry into the hypothetical situation regarding health expectations, life expectancy, and so on, and how much gets replaced by the content of the hypothetical scenario. Clearly this problem can be addressed by being as explicit as practicable about the scenarios being discussed.

Related to the above point is the issue of subjects not being *able* to put themselves into the circumstance described in the hypothetical example. They may be unfamiliar with the symptoms of a condition, or the difficulties faced with a certain disability, and moreover, their beliefs about these factors and their severity will be heterogeneous amongst subjects due to their differing knowledge and experience. Similarly, they may fully understand the technicalities of the situation, but not being able to put themselves into the situation in a psychological sense, or to appreciate what their actions would actually be in the situation and how these would affect their wellbeing. This problem is related closely to the concepts of projection bias (Loewenstein, O'Donoghue, and Rabin 2003) and affective forecasting (Wilson and Gilbert 2005). The individual for example may not appreciate that while they would be highly distressed to have to rely on a wheelchair to get around at first, they would become accustomed to it over time, both psychologically and through behavioural changes.

Unfamiliarity with the *type* of choices being asked of the subject may be another confounding factor. People may not make decisions using formal optimization routines like a computer, but rather make decisions using a variety of environment-specific rules and heuristics that become optimal over time through adaptation, as described by Gigerenzer (2001) as an 'adaptive toolbox'. So if people are not familiar with the idea of trading-off health for money for example, due not only to their limited tradability, but also due to the fact that they have always operated in an environment with public health care, then they may not have the tools to make the optimal decision for themselves without practice and feedback. Furthermore, unfamiliarity with decisions context may make subjects more prone to the coherent arbitrariness discussed by Ariely, Loewenstein, and Prelec (2004).

Since health states are something that are felt over a certain duration, then it may be inappropriate to consider a health state to be in effect at a single point in time. In other words if an individual is asked about a hypothetical one month in an aversive health state (perhaps compared with another longer period at a future time), then it may be important to note that intertemporal discounting will be occurring *within* that one month period. Of course this issue is not unique to the health domain, since a monetary reward will similarly not be spent immediately upon receipt. But the issue is more likely to occur with the types of questions posed in the health domain.

One of the major confounds of eliciting intertemporal discounting measures for consumption or money is the potential for individuals to reschedule their consumption, and to invest in outside options, as discussed in Section 3.2.2. Health is generally less readily tradable over time than is money, and it is also less tradable for money than many other goods (but of course still tradable in some contexts), and this in fact may be an advantage when it comes to the elicitation of discount rates. Since assumptions regarding the tradability of health across time and for money are likely to be heterogeneous across individuals, then it would be best for elicitation questions to be as explicit as practicable about tradability, so that its effect can be homogenized. Chapman (2002) finds evidence of higher agreement between discount rates for money and health when tradability was made more explicit.

3.3.2 Domain Independence

Most theoretical models of intertemporal preferences consider some form of discounting applied to utility, often proposing a constant discount rate for utility. Since utility is not directly measurable, empirical applications often have estimated discount rates with respect to money. This creates many problems, for example those caused by the fact that utility may be a non-linear function of wealth, and importantly the fact that wealth is tradable between periods. While it may seem that an individual who much prefers receiving money now to later has a high discount rate, it could also be the result of their expectation of being able to receive a high interest rate on the money, their expectation that in the future they will be much wealthier and hence will have a lower marginal utility of wealth, and many other potential explanations.

Similar yet somewhat distinct arguments apply to the discounting of future health states. There are a myriad of reasons why intertemporal discounting for health would differ from intertemporal discounting of utility, and indeed from the more commonly estimated intertemporal discounting for wealth. However, the greater the extent that wealth can be simply traded for health, the more similar the discount rates for wealth and health would become. Thus there is theoretical uncertainty regarding the relationship between intertemporal discounting for health and for wealth, and a small programme of research has investigated this issue. The results are important for many reasons, including that it is generally much easier to measure intertemporal discount rate in relation to money, so these are often used to proxy for intertemporal discounting of health in applied research.

Chapman and Coups (1999) within their study of flu-vaccine acceptance obtained measures of both monetary and health discounting. They found a moderate correlation between similarly stated monetary and health intertemporal choice responses, but little correlation of either with a health sequence measure. Interestingly, they found the monetary discount rate to have more explanatory power than the health discount rate for acceptance of the flu vaccine.

Based on the hypothesis that previous results comparing health and monetary discounting could have been driven by the fact that responding to the monetary questions was a familiar task, whereas thinking about unfamiliar health states may be difficult, Chapman, Nelson, and Hier (1999) conducted experiments to compare discount rates in the domains of money, a familiar health issue and an unfamiliar health issue. Two different experiments eliciting discount rates both found that there were moderately high correlations between the two different health domains, but little correlation between each health domain and the monetary domain.

Lazaro, Barberan, and Rubio (2001) (and Lazaro 2002) find in both the context of decisions regarding private outcomes and decisions regarding social outcomes, that discount rates in the health domain are higher than those in the monetary domain.

Theory would predict that discount rates would be similar across the health and monetary domains in situations where money could be readily traded for health. A study by Chapman (2002) found support for this view by explicitly giving a context where they were tradable. However even though being tradable attenuated the difference in estimated discount rate between domains, the difference was still evident.

Chapman and Elstein (1995) find that the magnitude effect and dynamic inconsistency, found often in the monetary domain, also seem to apply in the health domain. However, there is once again relatively low correlation between elicited discount rates in the health and monetary domains, supporting the hypothesis of domain-independence.

An important point is made by Chapman (1996a) regarding expectations, building on the theories regarding deviations from a reference utility level being more important than absolute values. Chapman suggests that the general expectations that wealth will increase over working lifetime, and that health will decrease with age could give rise to the empirically observed differences in discounting between the health and monetary domains. Specifically, decreasing sequences were found to be more strongly preferred in the health domain, as predicted by this hypothesis.

Chapman (1996b) examines the apparent domain independence between intertemporal discounting of health and money, through three experiments designed to address possible explanations. The results show that the observed domain independence cannot be accounted for by either the magnitude or the curvature of the utility function. Thus there is evidence of true domain independence, which the author suggests may be due to domain specific differences in cognition. Evidence is also shown that the delay, magnitude and sign effects are apparent for health discount rates in a similar manner than that often found for monetary discount rates.

3.3.3 Properties of Discount Rates in the Health Domain

Similar to estimates of discount rates in the monetary domain, the most robust results in the health domain appear to be the magnitude effect, the sign effect and dynamic inconsistency. This section provides evidence of these properties specifically in the health domain, as well as other properties that have been supported by empirical evidence.

Evidence of the magnitude effect has been shown by Chapman and Elstein (1995), and Chapman (1996b).

Dynamic inconsistency has been shown to occur in the health domain in studies such as Chapman and Elstein (1995), Redelmeier and Heller (1993), Cropper, Aydede, and Portney (1994), Khwaja, Silverman, and Sloan (2007), Christensen-Szalanski (1984), and van der Pol and Cairns (2010). These show evidence of a decreasing discount rate, or the delay effect, or in some cases they simply focuses on the inconsistency (which *may* still be caused by the delay effect).

The hypothesis that the sign effect is evident in discounting in the health domain is supported by Chapman (1996b), MacKeigan et al. (1993) and Khwaja, Silverman, and Sloan (2007).

The broad consensus of the research programme discussed in the previous subsection is that there is evidence that the discount rates applied in the health domain are different to those applied in the monetary domain. Some results show that individuals exhibit higher discount rates with regard to health compared to money, with such evidence provided by Lazaro, Barberan, and Rubio (2001),Chapman and Elstein (1995). No clear direction of the difference is evident in Chapman (2002). And the opposite result is found by West et al. (2003). However these directional results may simply be driven by factors such as the magnitude effect, since the magnitude of a health gain or loss that is asked about is normally quite different to the magnitude of money amounts, and in any case what is an equivalent magnitude is highly subjective.

In many countries there is a large amount of public provision of health services, and thus there are many decisions regarding health that are taken out of the market's (and individuals') hands, and are made on behalf of society. Thus in the case of health, many are interested in how individuals' intertemporal preferences for society differ from their intertemporal preferences for themselves. This programme of research has been contributed to by papers such as Chapman (2002), and Cairns and van der Pol (2000).

3.4 Construction of Intertemporal Discounting Questions

3.4.1 Background

Later in this chapter, and in Chapters 4 and 5, data is analysed from the Spring 2008 South Australian Health Omnibus Survey (SAHOS). The SAHOS is a survey that has been conducted annually since 1991 by the Department of Health through interviews with a sample of South Australians, providing around 3000 cross-sectional observations. The random selection process, together with provided weights, cam provide estimates that are representative of the South Australian Population (aged 15 and over). This dataset includes basic demographic and health information, and questions on health, lifestyle and disease. The survey has been discussed in Wilson, Wakefield, and Taylor (1992).

Two questions were placed by me in the survey to elicit intertemporal discounting measures in the monetary and health domains. The data attainment methodology for the discounting variables can be described as an 'Artefactual Field Experiment', using the taxonomy of Harrison, Harstad, and Rutstrom (2004), which means it is similar to the style of a lab experiment in terms of the questions asked, with the added advantage of using a representative sample of respondents rather than the common samples of experimental labs such as university students. Many studies that elicit discounting behaviour occur in 'experimental' settings with convenience samples, so the use of a representative sample here is important as it will more accurately examine the phenomena analysed as they really exist in the wider population.

The questions used borrow heavily from the previous studies of Chapman and Coups (1999), and Chapman (2001), attempting to maintain comparability of results where possible. However the questions used here differ from those from the previous studies is many ways, in particular their construction was educated by the empirical and theoretical results of previous studies, and attempts were made to capture as much relevant variation in intertemporal preferences as possible, while minimizing the effect of the potential biases and confounds that have been discussed in previous sections.

The questions are presented below, followed by a discussion of their interpretation, and various considerations that went into their construction.

3.4.2 The Questions

Question 1 (Intertemporal Choice in Monetary Domain)[1]

Imagine that you just received a speeding ticket. This means you have to pay a fine in cash. You can either pay a $200 fine today, or can delay the payment and pay twelve months from today, but you may have to pay a larger fine if you delay it.
Which of the following would best describe your choice?

A) I would prefer to pay the fine now.

B) I would prefer to pay in twelve months but only if I did not have to pay more than:
i) $200
ii) $220
iii) $240
iv) $260
v) $280
vi) $300

C) I would prefer to pay in twelve months even if I had to pay more than $300.

[1]The question names were *not* included in the survey, but have been included in this presentation of the questions to facilitate references to the questions.

Question 2 (Intertemporal Choice in Health Domain)

Imagine that you have just been diagnosed with a new disease that does not cause any symptoms, but will kill you if untreated. Luckily, there are two drugs available that will completely cure you, drug X and drug Y.
Both drugs must be taken weekly for two years and will lead to a complete cure after completion.
Unfortunately, both drugs have side effects.
Both drugs will cause a high fever, dry itchy skin and diarrhoea to the same extent during the period that you are affected by side effects.
Drug X will give you side effects for the first 10 days only.
Drug Y will give you side effects beginning after one year has passed, these will also only last for a short time: that is a 10 days or a few days more (the exact duration would be told to you with certainty before you make your decision).
Which of the following would best describe your choice?

A) I would prefer to take Drug X.

B) I would prefer to take Drug Y, but only if the period that it causes side effects in no longer than:
i) 10 days
ii) 11 days
iii) 12 days
iv) 13 days
v) 14 days
vi) 15 days

C) I would prefer to take Drug Y even if the period that it causes side effects is greater than 15 days.

Respondents also had the opportunity to refuse response to the questions.

3.4.3 Elicitation Procedure

For the empirical usage of these data that is intended, it is important to capture as much variation in intertemporal preferences as possible, and thus it was considered that the methodology used should be one that elicits a discount rate. Further, since pricing and matching tasks complicate the elicited discount rate by making it a discount rate over a certain scale, onto which preferences will be heterogeneously mapped, they were also excluded as potential methodologies. Thus the main choice regarding methodology was to choose between the use of closed-ended choice tasks or open-ended questions.

The majority of studies in the same vein as this one have been undertaken either in experimental settings, or as small sample surveys. Thus they have had more freedom in terms of the complexity of questions that they ask. Since the unusual advantage of this particular study is the fact that the intertemporal choice questions are only a small part of a large sample health survey, this means that there were significant constraints on the size of the questions asked, and similarly on the amount of cognitive effort that could be asked of the respondents. Thus the questions needed to be of a form that would deliver as much useful information as possible from a small number of questions, and at the lowest cognitive effort possible. Of course reducing the cognitive effort involved in answering questions is also obviously important in any situation to make sure that respondents are capable of answering in line with their true preferences.

The question format selected for these survey question sits somewhere between the extremes of closed-ended and open-ended tasks. It attempts to derive as much information as possible from a single question like an open-ended task, but asks the respondent to choose between given options to minimize cognitive effort, as in closed-ended tasks. The questions are similar in nature to those used by Chapman and Coups (1999), but do away with the cognitively difficult concept of an explicit indifference point. The questions are similar in nature to a discrete choice experiment, but due to limitations caused by implementation costs in a large survey setting, a single response is used to determine the switching point.

The general advantages and disadvantages of closed-ended and open-ended question methodologies of elicitation have been discussed in Section 3.2.4. For open-ended questions, a point estimate can be obtained, and they are more statistically efficient. However it was noted that they are more cognitively demanding, and thus results may not reflect true preferences, particularly if the respondent has little incentive to respond correctly. Since the questions are to be asked within a large-sample survey, with little time for detailed explanation and little time for the respondent to think about the questions, and there are no financial incentives to supply the 'correct' answer, the risk of not obtaining 'true' preferences seems particularly high.

The questions were framed as much as possible in terms that would be natural for the respondent to understand from their own life experiences. So they were given believable scenarios and asked for a response in natural language, rather than asked extremely abstract questions about 'indifference points'. In particular in the health question, the scenario described involved a health state that was described as a confluence of conditions to which most respondents would be familiar. As much detail as possible was also given here about the baseline health state, and the exact effects of the choices, to minimize the problems of different interpretations discussed in a previous section.

The questions were framed as losses rather than gains, which have been found to be discounted differently to one another. The reason that losses were chosen is that they seemed to be more naturally appropriate for health decisions that are to be investigated. When thinking of preventive health measures such as diet, exercise, vaccinations or other preventive treatments, it seems natural to think of the painful injection or diet as a current cost (i.e. loss), and the potential future health problems as future costs. Essentially it is assumed that most people would see *not* taking costly preventive health measures, and having a healthy future, as their reference points. This assumption is of course not important to the analysis.

Congruence between the questions was also a major consideration from the outset. For comparability between the discount rates elicited from the questions, it makes sense that both questions allow for the same distinguishable ranges of discount rates. Similarly, it was the choice of treating the health scenario as a loss rather than a gain which was carried over to the monetary question to make that a loss also.

Table 3.1: Implied Monetary Discount Rates

Choice	Possible Range of ρ
A)	$-1 < \rho \leq 0$
B)i)	$0 \leq \rho \leq 0.05$
B)ii)	$0.05 \leq \rho \leq 0.15$
B)iii)	$0.15 \leq \rho \leq 0.25$
B)iv)	$0.25 \leq \rho \leq 0.35$
B)v)	$0.35 \leq \rho \leq 0.45$
B)vi)	$0.45 \leq \rho \leq 0.5$
C)	$\rho \geq 0.5$

3.4.4 Imputation of Discount Rates

Consider first Question 1, in the monetary domain. Let $\$x^{now}$ denote $\$x$ paid now, and $\$x^{1year}$ denote $\$x$ paid one year from now. Define the money discount rate ρ to be the monetary discount factor that would have the individual indifferent between paying $\$x$ now and $\$y$ one year from now. i.e. $\$(-x)^{now} \sim \$(-y)^{1year}$ if and only if $-x = \frac{1}{1+\rho}(-y)$

In other words, if an individual has a money discount rate of ρ in the above expression, then they will prefer to pay $\$x$ now to any amount greater than $\$y$ one year from now.

Thus from each individual's decision in Question 1, it is possible to impute a range of potential discount rates of this exponential discounting form. These are shown in Table 3.1. Note that these discount rates are monetary discount rates, not the pure utility discount rates upon which much of the theory of intertemporal discounting is usually based on. The table gives the potential ranges of annual monetary discount rates that would lead to

Table 3.2: Implied Health Discount Rates

Choice	Possible Range of ρ_H
A)	$-1 < \rho_H \leq 0$
B)i)	$0 \leq \rho_H \leq 0.05$
B)ii)	$0.05 \leq \rho_H \leq 0.15$
B)iii)	$0.15 \leq \rho_H \leq 0.25$
B)iv)	$0.25 \leq \rho_H \leq 0.35$
B)v)	$0.35 \leq \rho_H \leq 0.45$
B)vi)	$0.45 \leq \rho_H \leq 0.5$
C)	$\rho_H \geq 0.5$

selection of each possible response, under the assumption of exponential discounting over money in the required range, and that decision makers select the choice closest to their indifference point.

Similarly, the discount rate for health, ρ_H, can be defined by an analogous indifference relation to that of the monetary discount rate, except here x and y specify sequences of health.

$(-x)^{now} \sim (-y)^{1year}$ if and only if $-x = \frac{1}{1+\rho_H}(-y)$

An additional complication in the case of imputing ρ_H is that the question refers to *sequences* of health states, and thus there may be intertemporal discounting occurring within those sequences. However the effect on the estimated discount rates is very small, so Table 3.2 ignores this effect in the calculation of the implied health discount rates. This practice has been common in similar studies such as van der Pol and Cairns (2001), Lazaro (2002), and van der Pol and Cairns (2008).

Thus Table 3.2 gives the approximate ranges of annual health discount rates that would lead to the selection of each possible response, under the assumption of exponential discounting over the relevant health states, and the assumption that decision makers select the choice closest to their indifference point, and ignoring the relatively minor impact of intra-sequence discounting.

3.4.5 Selecting an Appropriate Range for Discount Rates

There is no normative prescription in economic theory regarding what rate of discounting is appropriate. While the survey questions provide responses that allow for choices based on *any* possible discount rate, the closed-ended question format requires the selection of choices in such a way that the resulting data will only enable the ability to distinguish between particular ranges of discount rates. Thus, in selecting the values in the questions asked the objective was to provide questions that give the ability to distinguish between as much meaningful variation as possible in heterogeneous individuals' implicit discount rates. As with all choices in the construction of these questions, it is also important to be mindful of the constraints of implementation costs and subjects' cognitive effort.

Firstly, the constraint of implementation costs means that the number of options given must be made as small as possible, while still allowing for the capture of sufficient meaningful variation in intertemporal discounting. The minimization of choices is of course also important to reduce the cognitive effort of the subjects. Having equal spacing between the options was also considered an important criteria, as it would make it easier for subjects to understand and respond to the questions. Finally in respect to ease of understanding, it would be better if the options seemed like natural values for the relevant scenarios.

Estimates of discount rates from previous research differ tremendously, Frederick, Loewenstein, and O'Donoghue (2002) for example in a review of previous studies found discount rates between -6% and infinity. As discussed in previous sections, there are regularities is the differences in discount rates based on the magnitudes, sign and delay of the outcomes, as well as their domain and other characteristics, so the selected discernable ranges will be based on the findings of studies that are as similar as possible on these characteristics.

Since the focus of this study is on health, a benchmark is used of the commonly found implied discount rates in the health context. According to Gyrd-Hansen (2002), estimated discount rates range between 2% and 45%, while a different review by Cairns (2006) suggests that the majority of estimates lie between 2% and 25%. While there are some studies that have found much larger implied discount rate and so it could be expected to find individuals with these, it is more important to target the discrimination between ranges to the area in which the majority of rates are expected to be found. For example Chapman and Coups (1999) structured their questions in such a way that they could not discriminate between discount rates between zero and a 400% annual discount rate, and the low sensitivity of their discounting variable impaired the use of it in their applied context.

In particular in the monetary domain, where the outcome of interest is readily tradable at known personal borrowing and lending rates, respondents may simply maximize the present value of the income streams and use field opportunities based on their own borrowing and lending capacities and interest rates to reschedule their consumption (Cubitt and Read 2007). Thus it is important to include the range of responses that would be expected under this assumption, as well as other responses that can show evidence against that assumption.

It is important to allow for negative and zero discount rates in the health domain, which until recently was not done in closed-ended choice methodologies (van der Pol and Cairns 2000). Indeed often a large number of subjects will fall into these categories, Chapman and Coups (1999) had 85% and 83% of participants expressing zero time preference for health and money respectively, although since their questions did not allow for negative time preference, these values may incorporate that too.

Based on the issues discussed above, it was decided to use questions that allow for the discrimination between discount rates that are negative, and discount rates in a variety of ranges up to 50%. One notable weakness is that an exactly zero discount rate cannot be separately discriminated, but will come into the ranges of a very small positive discount rate or negative discount rate. This is an unfortunate disadvantage of the elicitation methodology, since a zero discount rate would lead to perfect indifference between the timing of an outcome, and perfect indifference is difficult to elicit within natural choice-based questions. Of course one could attempt to do so by offering an option of 'I am completely indifferent to the timing at the same value', but there would then be some concern that this category would also be selected by those who did not understand the question or who did not put in the cognitive effort to think about it properly, and may serve as an anchor of an appropriate answer.

3.4.6 Interpretation of Elicited Discount Rates

The estimates of ρ and ρ_H are estimates of the parameters as they are defined in this chapter, that is a discount rate over money and a discount rate over ill-health respectively. They are also based on the assumptions of exponential discounting over the relevant outcomes. Even under the assumption that all individuals can be described by the theoretical Discounted Utility model of exponential discounting of utility, this does not mean that discounting will be exponential for money and health, or that the elicited discount rates will be equal to the true utility discount rate. However, if utility was linear in money and health, then it *would* be possible to interpret the ρ parameters as estimates of the utility discount rate, and an exponential functional form for utility discounting would also carry over to the other domains. While a utility function is unlikely to be linear in health in money in general, it may be a reasonable assumption that the utility function is *approximately* linear in these arguments over the relatively small amounts considered.

Previous studies have found evidence of a sign effect, a magnitude effect, a delay effect, a domain effect, and other contextual factors in the elicitation of discount rates. Thus it may be more accurate to consider the estimated discount rates elicited in the specific terms that they were derived in. Thus ρ may not be *the* discount rate for money, but rather the discount rate for monetary losses between now and one year from now, over a particular range of magnitudes, and perhaps even in a particular context.

These problems may seem to make the elicited variable too context-specific to be of any use, but this is not so. Rather than an estimate of specific discount rate parameter, the elicited variables can be thought of simply as indicators of the relative intertemporal preferences of the respondents. If it is assumed that having a 'high' discount rate in the context of a certain magnitude of monetary loss between now and one year from now when receiving a fine, would be correlated with having a 'high' discount rate when it comes to making long-term investment decisions, then the variables ρ and ρ_H can be thought of as indicators of the generic construct of intertemporal preference, or strength of the respondent's preference for present consumption over current consumption.

Whether the indicators ρ and ρ_H are considered to be reflective or formative indicators (as defined in Jarvis, Mackenzie, and Podsakoff 2003) of the latent construct of intertemporal preference is an issue that is open to some debate. In other words, can the elicited discount rates be considered to be reflections of some stable construct of intertemporal preference, or is the latent construct of intertemporal preference more appropriately considered to be a function of context-specific discount rates. Assumptions regarding the nature of the indicators will be important for some of the statistical tests undertaken using them, but rather than make a subjective decision at this stage about how to treat the variables, it will be made clear throughout when empirical work depends on auxiliary assumptions about the nature of the indicators.

The construct validity of the intertemporal discounting variables, that is the degree to which they represent the intended aspects of intertemporal preference, can be assessed by looking at particular aspects of construct validity: convergent validity, discriminant validity, content validity, and nomological validity.

Convergent validity is the degree to which the indicator is similar to other indicators that it theoretically should be similar to. Under the reflective indicators assumption, the most appropriate comparison is between ρ and ρ_H. If they both are indicators of a stable trait of intertemporal preference, then there is reason to expect a strong relationship between the two indicators, and this can be tested. Discriminant validity of an indicator is based on the degree to which the indicator is dissimilar from other measures. There may be a concern for example that the elicited indicators of discounting could be highly correlated with education, due to their cognitive difficulty, which would be an indication of poor discriminant validity. This will be assessed in a later section.

The content validity of a variable refers to the degree to which the variable's construction is logically consistent with what it intends to measure. The content validity cannot be tested empirically, but instead is a reflection of the appropriate specification of the variable. The current section, including the preceding and following subsections, analyse the construction of the questions and the variable derivations. They address the issue of content validity by discussing the detail behind the variable construction, and thus provide support for the content validity of the derived variables.

Finally, the nomological validity of an indicator is the degree to which it behaves as expected within a system of relationships. Unfortunately, it is difficult to test the nomological validity of the variables separately from testing the appropriateness of the model in which the variables are applied. However, the results in Chapter 4 and Chapter 5 that find expected relationships between these intertemporal discounting indicator variables and health outcomes, can be seen as evidence of the nomological validity of the variables.

The assessment of the discriminant validity, content validity and nomological validity of the intertemporal discounting variables does not depend in any great part on the interpretation of the variables as reflective or formative indicators of intertemporal discounting. However, the assessment of the convergent validity of the variables certainly does. Assessing the convergent validity of the variables by looking for a relationship between the monetary domain and health domain indicators is only appropriate under the assumption that they are reflective indicators.

3.4.7 Discussion of Potential Biases and Confounds

This subsection will address many of the biases and confounds that complicate the estimation of discount rates that were discussed in previous sections. How much of a problem the issue could potentially be will be discussed, as well as any steps that were taken in the construction of the questions to minimize that particular issue.

The magnitude, sign and delay effects

The magnitude effect, sign effect, and delay effect, may be considered problems if the goal is to estimate a single utility discount rate. However, if the elicited discount rates are interpreted as context-specific, then they are less of a problem. The two remaining problems then are the impact of these three effects on comparisons between ρ and ρ_H, and the impact of these three effects on the relationship between the intertemporal discounting variables and other variables such as health outcomes.

With respect to minimizing the confounds of these three effects on comparison between domains, the questions were constructed so that each question considered the same sign and delay, thus reducing the impact of these effect on comparisons. With respect to magnitude however, no attempt was made to match the monetary and health magnitudes (which has been attempted by Chapman 1996b), since the extra questions required were not possible in the particular survey context.

An issue perhaps of more concern is the possibility that the discount rates elicited for specific magnitudes, signs, and delays may not be closely associated with the discount rates that are relevant for the health-affecting choices of interest. This could lead to difficulties in the estimation of relationships between intertemporal discounting and health outcomes. This depends crucially on the extent to which a high discount rate in the specified context is related to a high discount rate in other contexts. If the elicited indicators can be considered as accurate reflective indicators of an unobservable intertemporal preference trait, then they should be able to proxy for this trait in the relevant contexts.

Field opportunities and censored data

In the case of eliciting the monetary discount rate, the data may be censored by intertemporal trading opportunities that are unobservable to the researcher. While this may be the case, the fact that the discount rate ranges include the range of likely individual borrowing and lending rates, as well as higher rates, allows the possibility of censoring to be examined. In the case of the health discount rate, this problem should not be evident, since while in the real world health is tradable over time to some extent, the question's context regards specific health outcomes that are not tradable over time.

Risk preferences, expectations of changing circumstances and other confounds

Confounds such as risk preferences, expectations of future circumstances and other confounds that may affect the respondents intertemporal choices, but are not due to the pure rate of utility discounting, may affect the elicited discount rate. However, since the question of interest is how intertemporal preferences drive behaviour, rather than accurately estimating the abstract pure intertemporal discount rate, this is of little concern. If the survey questions are answered in a certain way based on the expectation of the respondent that they will be significantly more wealthy one year from now, then they should also be making their other lifestyle choices based on the expectation of being significantly more wealthy one year from now. So the elicited discount rate that incorporates these factors is in fact the measure that should be used to analyse health behaviours and outcomes.

Framing effects, difficulty answering, and strategic answers

Of course any way that a question is framed has the potential to impact the outcomes that it produces, so there is no way around that. The questions were constructed in a fashion in which they were framed in terms of decisions that would seem natural to the respondent, and thus are more likely to elicit responses reflecting their real world behaviours. As much explicit detail as practicable was also given with regard to describing the scenarios, to try to make sure all respondents were answering the same question from the same baseline situation. There would seem to be little to no reason for respondents to strategically answer in this context, so that is of very little concern.

3.4.8 Overall Appraisal of Questions

The main advantage of this data over that used in previous studies is the sample size, the heterogeneity of the respondents, and the rich source of data that these questions can be connected to. On the other hand, many of the data's weaknesses were generated by constraints imposed by using a large sample survey, both in terms of the implementation costs and the efforts made to reduce cognitive effort.

A high priority was put on ease of comprehension, and natural scenarios, rather than on statistical efficiency, since there is no point have a statistically efficient estimate of something that wasn't intended due to respondents misunderstanding or misinterpreting the questions. There are a lot of potential problems with the elicited variables, but this simply comes with the territory of eliciting indicators of intertemporal preference. While the potential problems are recognized, every effort has been made within the constraints of the study to elicit indicators that capture as much meaningful variation of intertemporal preferences as possible, and minimize biases and confounds as much as possible.

While steps were taken to minimize the biases caused by the issues discussed, the data validity can only be assessed on the grounds of its construction. Once again due to the constraints and costs of the particular survey methodology, it was not possible to include any extra questions designed to assess issues such as those discussed above.

3.5 Analysis of Data

3.5.1 Descriptive Statistics

The questions detailed in Section 3.4.2 were asked in the 2008 South Australian Health Omnibus Survey (SAHOS), which occurred in September and October 2008. The dataset contains 2824 respondents in total. Of these respondents, 212 did not answer one of the intertemporal choice questions, so only 2612 respondents from whom there are responses to both questions. In Chapter 4 and Chapter 5 a reduced sample is used consisting of 1868 respondents, due to the availability of variables for health, behaviour and demographics. For consistency, this same reduced sample is used throughout the analysis in the remainder of this chapter. Throughout this analysis the population weights provided with the dataset have not been used, since they are no longer appropriate for the reduced sample, and since in general the questions of interest are about variable associations rather than population estimates. This path was chosen since the aim is usually to estimate coefficients indicating the relationship between certain variables, for example the conditional marginal effect of being a discounter on BMI outcome. Maintaining the assumption that sample selection depends on the observed independent variables in the model, both unweighted and weighted regressions will be consistent and unbiased, however unweighted regression will be more efficient (Winship and Radbill 1994).

Some of the analysis is repeated in Appendix A using the full unrestricted sample of 2824 observations.

The reduced sample of 1868 observations is comprised of 54.87% females, and 45.13% males. The average age is 49.5, with a range from 15 to 94 years of age.

Tables 3.3 and 3.4 summarize the responses to monetary domain and health domain intertemporal choice questions respectively.

Table 3.3: Summary of Responses to Question One (Monetary Domain)

Response	Implied Range of ρ	Frequency	Percent
Prefer to pay the fine now	$-1 < \rho \leq 0$	1512	80.94
\$200	$0 \leq \rho \leq 0.05$	209	11.19
\$220	$0.05 \leq \rho \leq 0.15$	61	3.27
\$240	$0.15 \leq \rho \leq 0.25$	37	1.98
\$260	$0.25 \leq \rho \leq 0.35$	11	0.59
\$280	$0.35 \leq \rho \leq 0.45$	4	0.21
\$300	$0.45 \leq \rho \leq 0.5$	13	0.70
Prefer later still	$\rho \geq 0.5$	21	1.12

Clearly in both domains the responses are heavily skewed towards showing

Table 3.4: Summary of Responses to Question Two (Health Domain)

Response	Implied Range of ρ_H	Frequency	Percent
Prefer now	$-1 < \rho_H \leq 0$	1675	89.67
10 days	$0 \leq \rho_H \leq 0.05$	136	7.28
11 days	$0.05 \leq \rho_H \leq 0.15$	2	0.11
12 days	$0.15 \leq \rho_H \leq 0.25$	7	0.37
13 days	$0.25 \leq \rho_H \leq 0.35$	1	0.05
14 days	$0.35 \leq \rho_H \leq 0.45$	0	0.00
15 days	$0.45 \leq \rho_H \leq 0.5$	13	0.70
Prefer even longer extension	$\rho_H \geq 0.5$	34	1.82

negative or zero rates of discounting. The results are in fact quite similar to Chapman and Coups (1999), where questions similar to those used here were used. They found 83% of respondents expressed non-positive discount rates in the monetary domain, and 85% non-positive discount rates in the health domain.[2] Although the questions used in this survey were similar, it was not expected that the results would be similarly skewed, as the questions had been modified so that the discount rate elicitation was much finer towards zero. The confirmatory result here suggests that Chapman and Coups' 'zero time preference' findings were not simply an artefact of the fact that their question could not discern between a zero discount rate and annual discount rates up to 400%, but rather show that at least in the context of the scenario question, it may be that people do in fact not exhibit positive discount rates, or only exhibit very small discount rates.

When specifically looking for negative and zero intertemporal discount

[2]They say these express a 'zero time preference', missing the fact that the could also indicate negative discount rates.

rates for health, van der Pol and Cairns (2000) find a much smaller proportion of respondents with non-positive discount rates. However they also review the evidence from other studies, and while the results certainly vary significantly, there are clearly other studies with similarly high proportions of non-positive discounters.

The results in the monetary and health domains are somewhat similar in their pattern. The majority of respondents in the non-positive discounting range, the majority of the discounters in the lowest possible range, and then a general trailing off of numbers as the discount rate range increases, but a small increase at the higher ranges. However there seems to be less discounting in general in the health domain relative to the monetary domain. It is also worth noting that there is a much higher number of missing values in the health domain question, perhaps reflecting the increased difficulty for respondents of answering such a question in an unfamiliar domain.

Since only a small proportion of respondents gave answers suggesting discount rates in each of the higher ranges, it may be interesting to group those who show positive discount rates together to create a binary indicator variable.

Two variables which will be used later in the thesis are defined here as follows. PDR-M takes the value of '1' if the respondent showed evidence of a positive discount rate in the monetary domain, otherwise it takes the value '0'. PDR-H takes the value of '1' if the respondent showed evidence of a positive discount rate in the health domain, otherwise it takes the value '0'.

So from the previous tables it is easy to see that 19.06% of respondents show evidence of a positive discount rate in the monetary domain, and 10.33% of respondents show evidence of a positive discount rate in the health domain. These 'monetary discounters' and 'health discounters' are interesting subgroups to contrast to their non-discounting comparators.

3.5.2 Association with Demographic Variables

Table 3.5 simply compares the (unweighted) mean values of a number of demographic and health variables, across the subsamples of discounters and non-discounters in each of the two domains. Note that since throughout this thesis all analysis is generally undertaken using unweighted data, for example the means presented should not be interpreted as estimates of the population means, but rather as characteristics of the sample used, which potentially differ from the population in systematic ways.

Monetary discounters are on average younger than their non-discounter comparators, while in the health domain the converse is true, with health discounters on average older than non-discounter. In both domains males are slightly more likely to be discounters than females. There are few noticeable differences in the education and income levels between discounters and non-discounter, which may be of some surprise since there are reasons to expect a relationship between these variables. 'Inadequate' health literacy, as measured by the Newest Vital Sign measure, seems to be positively associated with discounting in the health domain.

The mean BMI of the discounting and non-discounting sub-samples using the monetary domain measure differs in the expected direction, with discoun-

Table 3.5: Variable Means by Discounter and Non-Discounter Sub-samples

	PDR-M=1	PDR-M=0	PDR-H=1	PDR-H=0
Age	44.58	50.67	53.82	49.00
Female	0.506	0.559	0.508	0.553
Australian Born	0.787	0.737	0.741	0.747
Highest Qualification				
Bachelor degree or higher	0.202	0.204	0.166	0.208
Certificate/Diploma (>1FTE)	0.135	0.148	0.145	0.146
Certificate/Diploma (≤1FTE)	0.129	0.120	0.088	0.125
Trade/Apprenticeship	0.121	0.133	0.135	0.130
Left school after 15, still studying	0.062	0.030	0.047	0.035
Left school after 15	0.225	0.231	0.238	0.229
Left school at 15 or less	0.098	0.123	0.176	0.112
Still at school	0.028	0.012	0.005	0.016
Household Income Range				
≥ $100000	0.188	0.200	0.104	0.209
$80001-$100000	0.107	0.114	0.109	0.113
$60001-$80000	0.140	0.142	0.161	0.139
$50001-$60000	0.073	0.088	0.083	0.085
$40001-$50000	0.090	0.083	0.093	0.083
$30001-$40000	0.079	0.086	0.093	0.084
$20001-$30000	0.112	0.126	0.171	0.118
$12001-$20000	0.149	0.118	0.130	0.123
≤ $12000	0.062	0.044	0.057	0.046
Functional Health Literacy				
Adequate	0.621	0.585	0.528	0.599
At Risk	0.228	0.230	0.207	0.232
Inadequate	0.152	0.185	0.264	0.168
Selected Health Variables				
Body Mass Index (BMI)	27.93	26.83	27.12	27.03
Binary Smoking Indicator	0.230	0.154	0.140	0.172

ters having a higher BMI. The proportion of smokers, is also larger for the monetary discounters. On the other hand using the health domain indicators the mean health outcomes are more similar.

To more robustly analyse the association between discounting behaviour and demographics, multivariate regression can be used to partial out the effect of certain variables. The following analysis in Table 3.6 uses the variables from Table 3.5 that are more naturally considered as demographic variables or exogenous characteristics. In other words the health related variables are not included, as their association with the discounting variables as likely to be due to causation from the direction of discounting to health.

Columns (1) and (2) of Table 3.6 show the estimates from linear regressions of the demographic characteristics on the discount rate estimates themselves. In order to obtain a suitable continuous variable from the range estimates, the midpoint of each range was used, except on the first and last options where the rates were assumed to be 0 and 0.5 respectively.

Columns (3) and (4) of Table 3.6 follow by showing regression estimates of the marginal effects of the demographic characteristics on the binary indicators of discounting. Due to the binary dependent variables probit estimation is used for the presented results, but the results do not change noticeably if a different binary dependent variable estimation method is used such as logit.

These results show that the majority of the demographic variables are not significantly associated with the discounting measures. Furthermore, the low R-squared values suggest that demographic characteristics explain only a small fraction of the variation is the elicited discounting measures. As

Table 3.6: Regression Estimates of Demographics on Discounting Variables

Dependent Variable	(1) ρ	(2) ρ_H	(3) PDR-M	(4) PDR-H
Age	-0.00101***	8.22e-05	-0.00383***	0.00107**
	(0.000124)	(0.000128)	(0.000628)	(0.000475)
Female	-0.00301	-0.00549	-0.0437**	-0.0192
	(0.00371)	(0.00384)	(0.0191)	(0.0146)
Australian Born	0.00911**	0.00374	0.0245	0.00805
	(0.00411)	(0.00426)	(0.0208)	(0.0155)
Highest Qualification				
Bachelor degree or higher		(Base Group)		
Certificate/Diploma (>1FTE)	0.00213	-0.000995	-0.00376	-0.00424
	(0.00619)	(0.00641)	(0.0316)	(0.0243)
Certificate/Diploma ($\leq$1FTE)	-0.00410	-0.00664	-0.00357	-0.0231
	(0.00659)	(0.00682)	(0.0332)	(0.0239)
Trade/Apprenticeship	-0.000473	0.000462	-0.0283	-0.0102
	(0.00661)	(0.00684)	(0.0313)	(0.0249)
Left school after 15, still studying	0.0132	0.00166	0.0631	0.0473
	(0.0103)	(0.0106)	(0.0563)	(0.0500)
Left school after 15	-0.000266	-0.00270	-0.0192	-0.000105
	(0.00579)	(0.00599)	(0.0287)	(0.0231)
Left school at 15 or less	-0.00263	-0.000270	-0.0315	0.0262
	(0.00731)	(0.00756)	(0.0350)	(0.0313)
Still at school	0.00330	-0.0141	0.0212	-0.0476
	(0.0153)	(0.0158)	(0.0758)	(0.0487)
Household Income Range				
$\geq$ \$100000		(Base Group)		
\$80001-\$100000	0.00439	0.0101	0.00622	0.0723*
	(0.00661)	(0.00684)	(0.0346)	(0.0381)
\$60001-\$80000	0.000395	0.00899	0.0320	0.0871**
	(0.00627)	(0.00649)	(0.0345)	(0.0368)
\$50001-\$60000	0.00159	-0.00191	0.00577	0.0622
	(0.00734)	(0.00759)	(0.0391)	(0.0412)
\$40001-\$50000	0.0130*	0.0133*	0.0570	0.0748*
	(0.00748)	(0.00775)	(0.0436)	(0.0432)
\$30001-\$40000	0.00915	0.0134*	0.0427	0.0710*
	(0.00756)	(0.00782)	(0.0435)	(0.0428)
\$20001-\$30000	0.0195***	0.0140*	0.0811*	0.0830**
	(0.00712)	(0.00737)	(0.0438)	(0.0409)
\$12001-\$20000	0.0256***	0.00936	0.166***	0.0380
	(0.00732)	(0.00758)	(0.0484)	(0.0366)
$\leq$ \$12000	0.0248**	-0.00211	0.189***	0.0463
	(0.00988)	(0.0102)	(0.0680)	(0.0502)
Functional Health Literacy				
Adequate		(Base Group)		
At Risk	0.00826*	0.000840	-0.0108	-0.0155
	(0.00459)	(0.00475)	(0.0230)	(0.0171)
Inadequate	0.0110**	0.00456	-0.0181	0.0232
	(0.00553)	(0.00572)	(0.0275)	(0.0225)
Constant	0.0531***	0.00480		
	(0.00811)	(0.00840)		
Observations	1868	1868	1868	1868
R-squared	0.050	0.010		
Pseudo R-Squared			0.039	0.029

Columns (1) and (2) show coefficient estimates, (3) and (4) show marginal effects
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.7: Contingency Table for Binary Discounting Indicators

		Health Discounter (PDR-H)		
		No	Yes	Total
Monetary Discounter (PDR-M)	No	1375	137	1512
	Yes	300	56	356
	Total	1675	193	1868

a result the specific coefficient estimates, and levels of significance are of little interest. If the goal was to find out exactly what kind of people had high discount rates, then these results would be disappointing. However the main goal of this thesis is to look at how these discounting variables are related to health behaviours and outcomes, and to this end the results from Table 3.6 are a good sign. The fact that the discounting variables cannot be explained by other demographics suggests that the elicited measures are in fact a measure of a distinct concept, which is hoped to be a true reflection of their intertemporal preferences. Using more technical terminology, the low partial correlations between the discounting variables and other variables is evidence of the discounting variables having good discriminant validity.

3.5.3 Domain Independence

With data on discounting in two domains, for money and health, it is possible to compare the measures. Tables 3.7 and 3.8 show contingency tables for the discounting responses and the derived binary indicator variables.

Looking first at the raw responses, and their implied discount rates. The implied discount rate variables have a Pearson Correlation Coefficient of 0.007. Since the association between the variables may not be linear, it

Table 3.8: Contingency Table for Discounting Responses

		ρ_H								
		A	Bi	Bii	Biii	Biv	Bv	Bvi	C	Total
	$-1 < \rho \leq 0(A)$	1375	94	2	5	1	0	9	29	1512
	$0 \leq \rho \leq 0.05$ (Bi)	169	33	0	0	0	0	2	5	209
	$0.05 \leq \rho \leq 0.15$ (Bii)	51	5	0	1	0	0	2	2	61
	$0.15 \leq \rho \leq 0.25$ (Biii)	36	1	0	0	0	0	0	0	37
ρ	$0.25 \leq \rho \leq 0.35$ (Biv)	11	0	0	0	0	0	0	0	11
	$0.35 \leq \rho \leq 0.45$ (Bv)	3	0	0	1	0	0	0	0	4
	$0.45 \leq \rho \leq 0.5$ (Bvi)	12	0	0	0	0	0	0	1	13
	$\rho \geq 0.5$ (C)	18	3	0	0	0	0	0	0	21
	Total	1675	136	2	7	1	0	13	34	1868

is also informative to look at the non-parametric Spearman Rank Correlation Coefficient, which is 0.078. By either measure the degree of association of these variables isn't high. It can be readily seen from the contingency table, that many of the health-domain discounters were not monetary domain discounters, and vice versa. Due to the high number of empty cells, it is not appropriate to use the standard tests of independence such as Pearson's Chi-Squared test.

The phi coefficient[3] between the binary indicator variables is 0.086, once again showing a low degree of association. However Pearson's Chi-Squared test rejects the null hypothesis of independence (p-value:0.000), suggesting that there is some association, although it may be small in magnitude.

These results could be considered evidence against the convergent validity of these variables under the interpretation of the variables as reflective

[3]In the binary variable case, the Pearson and Spearman coefficients are by definition equal and identical to the 'phi coefficient', which is denoted as such to emphasise the special characterisitics in this case.

indicators that should both reflect the same stable trait of intertemporal preference. However this comparison would not be relevant under the interpretation of the variables as formative indicators of intertemporal preference, whereby ‘intertemporal preference’ is considered the amalgamation of various individual variables.

The evidence presented here supports the findings of ‘domain independence’ that were discussed in Section 3.3.2. Although the evidence is not that the variables are literally independent, there is clearly a very low correlation between them, so an individual’s discounting behaviour in the monetary domain can often be quite different to their discounting in the health domain.

3.6 Conclusion

This chapter has described in detail the construction of the stated-preference indicators of intertemporal discounting that will be used in Chapters 4 and 5. Preliminary analysis of these variables indicates that the construct that they represent cannot be explained away by demographic variables and personal characteristics. It was also found that many individuals did not show much evidence of impatience, or a positive discount rate at all. Another important result was that the health domain measures were not highly correlated with the monetary domain measures. Thus it may be important to use both in further analysis.

Due to the general difficulty of eliciting discount rates, as well as other constraints of cost, time and cognitive complexity, it is not contested that the indicators ultimately derived are perfect. However they are clearly of use, and are the best possible measures available within the situational constraints. Whether the variables can be considered as accurate estimates of individuals' true utility discount factors, or whether they proxy for discounting behaviour in a different way, they will still be of great use in the following empirical analysis.

Chapter 4

Body Weight Outcomes and Intertemporal Discounting

4.1 Introduction

Theory, and common-sense, suggest that people who are more present-focused will be less likely to make choices that reduce their present enjoyment but improve their health, since many of the benefits of good health will occur in the future. This issue is highly relevant with regard to body weight behaviours and outcomes, and the theory and evidence of this have been discussed in Chapter 2.

It is surprising therefore that evidence of a positive relationship between the rate of intertemporal discounting and unhealthy body weight outcomes has not been more robustly found in the literature. This chapter analyses the relationship between discounting and body weight outcomes, with a number of innovations relative to the previous literature, to show that there is a significant relationship between these two variables, and to analyse the form of this relationship.

It is important that the variables representing intertemporal discounting are valid measures of this concept, and to this end two stated-preference questions to elicit intertemporal discounting were developed and analysed in Chapter 3. Due to evidence of domain independence in elicited discount rates, it may be important to use a variable representing intertemporal discounting in the health domain, rather than the standard monetary domain indicators. Whether or not a health domain indicator of intertemporal discounting is an important determinant of body weight outcomes has not previously been tested in the literature. This chapter finds that the monetary domain measure of intertemporal discounting is more strongly associated with body weight outcomes than the health domain measure, similar to the results found in other contexts (See for example Chapman and Coups 1999).

Another contribution of this chapter is in the analysis of differences in the association between intertemporal discounting and body weight across the distribution of body weight outcomes. While for an overweight individual there is a health benefit to lowering their BMI, on the other hand an underweight individual might receive a health benefit from increasing their BMI. Thus 'costly investments' in future health (such as a healthier diet than desired by tastes alone) may have effects of increasing the BMI of an underweight individual, and decresing the BMI of an overweight individual. A higher rate of intertemporal discounting is expected to be associated with a lower rate of investment in health, so could be associated with BMI in opposite directions for underweight and overweight individuals. This effect may have been present and uncontrolled for in previous studies that had difficulty finding associations between body weight outcomes and intertemporal discounting.

After some preliminary discussion of an appropriate framework, and a description of the data, this chapter analyses the relationship between intertemporal discounting and body weight outcomes. The estimated models should be interpreted as risk factor models, with the primary estimates of interest being the estimates of discounting as a risk factor for high body weight outcomes, holding the other control variables constant. The procedures used do not necessarily identify the direction of causality, but do establish the association between the variables, which are important in their own right.

Multivariate regression analysis of BMI on discounting variables and controls does find a significant relationship between the monetary domain indicator of discounting and higher BMI. However these conditional correlation results do not tell the full story about how the relationship might differ across body weight outcome groups. This problem is often addressed in the literature on body weight outcomes by considering separately the individual categorisations of 'underweight', 'normal weight', 'overweight' and 'obese', and the analysis presented here applies this approach to see how it affects the results of interest. However these categorisations are somewhat arbitrary, so it is perhaps more appropriate to apply an econometric technique that can account for the differences in estimated effect of explanatory variables on BMI across more points on the BMI distribution. To this end the technique of quantile regression estimation is employed, and it is found that there may be a stronger association between intertemporal discounting and body weight outcomes at the higher end of the BMI distribution, in particular in the 'obese' range.

Through a variety of methodologies, it is shown in this chapter that the indicator of intertemporal discounting in the monetary domain from Chapter 3 is positively associated with excess body weight outcomes. The estimated association of discounting as a risk factor for obesity and higher BMI is of a similar magnitude to the independent effects of income and education in all of the estimated models. So the evidence presented here shows that discounting is a risk factor potentially as important as these commonly recognised demographic risk factors for obesity.

4.2 Model and Empirical Implementation

4.2.1 A Simple Model of Body Weight Determination

The economic decisions that result in the determination of body weight are extremely complex. As such, when estimating an empirical model of body weight determination, there will necessarily be the need for simplifying assumptions, and perhaps reduced-form estimation of a broader structural model. This does not mean that an empirical implementation should consist of regressing a dependent variable representing body weight on a tenuously determined group of 'exogenous' variables. It is imperative that any estimated model be carefully derived from theory, to which end a simple model of body weight determination is presented in this section. Furthermore, interpretation of the results of reduced-form estimation, or estimation of very simple models, should take into account the inappropriateness of applying results to settings where the underlying structure is different.

The model presented below is essentially the model of Lakdawalla, Philipson, and Bhattacharya (2005) (also, Lakdawalla and Philipson 2009). It has been slightly modified and re-interpreted here as appropriate for the context.

The modifications to the model recognise the heterogeneity of individuals with respect to their preferences, and also how their consumption patterns translate to weight outcomes. To this end the utility and weight determination functions are allowed to vary across individuals, and this is made explicit through a vector of parameters.

While some studies have analysed differences in body weight or obesity among varying locations or time periods, the goal here is different. This chapter analyses the epidemiology of body weight within a certain population at a certain time defined by the data source (Adelaide in 2008), and the issue of interest is how differences at the level of individuals translate into differences in the conditional distribution of body weight. Thus in the model presentation it can be assumed that some more global variables such as food prices are constant.

An individual's period t utility, (4.1) depends on food consumption F, other consumption C, and weight W. Utility functions are unique and individual heterogeneity is represented by a vector of parameters θ. What it termed 'food consumption' for notational convenience, could be easily be re-interpreted as 'weight-increasing consumption'.

$$U(F_t, C_t, W_t; \theta) \tag{4.1}$$

$$W_{t+1} = (1-\delta)W_t + g(F_t; \gamma) \tag{4.2}$$

$$pF_t + C_t \leq Y_t \tag{4.3}$$

The transition equation for weight is specified in Equation (4.2), where δ is the depreciation rate for the weight stock (this can be thought of as the effect of basal metabolism), and weight can be affected by the consumption of food, according to a weight generation function $g(F_t; \gamma)$, where γ contains parameters reflecting individual heterogeneity.

The individual also faces a budget constraint (4.3), where Y is income, and p is the price of food.

It is assumed that individuals discount future utility with the standard exponential discounting form. The period discount factor for utility is denoted as β.

An individual's value function can be written as v, defined as below (4.4).

$$v(W_t) = \max_{F_t, C_t, W_{t+1}} U(F_t, C_t, W_t; \theta) + \beta v(W_{t+1}) \tag{4.4}$$

$$s.t. \quad pF_t + C_t \leq Y_t \tag{4.5}$$

$$W_{t+1} = (1 - \delta)W_t + g(F_t; \gamma) \tag{4.6}$$

Assuming that the function U is continuous, differentiable, strictly concave, and bounded, and that the function g is continuous and concave, the value function will be continuous and strictly concave (Stokey and Lucas 1989). Under those assumptions, the value function can be differentiated to yield the first order (4.7) and envelope conditions (4.8). The first order condition states that in the optimum, the marginal utility of food in period t must be equal to the marginal utility of other consumption in period t. The marginal utility of food is made up of the direct marginal utility, plus the marginal effect of food consumption on the value function through weight gain. The envelope condition requires that the marginal effect of weight on the current period value function be equal to the sum of the current period marginal utility of weight, and the discounted marginal effect of future weight on the value function.

$$U_{F_t}(F_t, Y_t - pF_t, W_t; \theta) + \beta g_{F_t}(F_t; \gamma) v'(W_{t+1}) = pU_{C_t}(F_t, Y_t - pF_t, W_t; \theta) \tag{4.7}$$

$$v'(W_t) = U_{W_t}(F_t, Y_t - pF_t, W_t; \theta) + \beta(1-\delta)v'(W_{t+1}) \tag{4.8}$$

Under a variety of reasonable assumptions[1], steady-state food intake $F^*(p, Y, \beta, \delta, \theta, \gamma)$ and steady-state weight $W^*(p, Y, \beta, \delta, \theta, \gamma)$ can be obtained as functions of exogenous variables. It is simple to obtain some comparative statics results, such as that W^* and F^* are both decreasing in p, and that higher income lowers W^* and F^* for the overweight, and raises W^* and F^* for the underweight (the latter results require specific restrictions on the functional forms not presented here).

In other words, an individual's steady-state body weight is some function of their income, the form of their utility function, the form of their weight determination function, the prices they face in the market, and their discount rate.

4.2.2 Empirical Model Specification

Due to the biological, social, and economic complexity of body weight determination, it would be very difficult to estimate a truly structural model of body weight determination. Even under the restrictions assumed to allow for the solution to the above theoretical model, the functional forms of the relationships between the exogenous variables and outcome variables are not well-defined. As such, the current best practice methodology when it comes to estimating models of body weight outcomes is through the use of an appropriately specified reduced form model. Recent examples of estimation of

[1]The most notable being that the full marginal utility of food, $U_{F_t}(F_t, C_t, W_t; \theta) - pU_{C_t}(F_t, C_t, W_t; \theta)$, is decreasing in weight. See Lakdawalla and Philipson (2009) for full details and discussion.

broad models of BMI and obesity determination include Chou, Grossman, and Saffer (2004) and Maennig, Schicht, and Sievers (2008).

Although it is not possible to directly apply the theoretical model of Lakdawalla and Philipson (2009) to the data, the results of that model are used to inform the selection of an appropriate reduced form specification. The model finds that steady-state weight is a function of the exogenous variables, $W^*(p, Y, \beta, \delta, \theta, \gamma)$. The research question of interest in this chapter can essentially be re-described as to look at how W^* depends on β, and of course the other exogenous variables need to be controlled for to do this. The empirical specification used for the estimations will use annual income to control for Y, differences in individuals' weight generation functions (γ) will be controlled for by controlling for age, sex, functional health literacy and education (these also may control for θ to some extent), δ is controlled for partly by age and sex, β is represented using stated-preference indicators of intertemporal preference, and it is assumed that market prices for consumption goods are constant across individuals (so p is a constant). The unobservable factors that cannot be controlled for are captured by an error term u_i, which includes factors such as genetics and unobservable variation in preferences. As well as being motivated by the theoretical model, the selection of these exogenous variables has been educated by other literature regarding determinants of body weight, which was reviewed in Chapter 2.

$$B_i = f(X_i, u_i) \tag{4.9}$$

The observed body weight outcome of the ith individual B_i is some function f of a vector of the observable explanatory variables X_i (age, sex, income, education, functional health literacy, intertemporal discounting), and a stochastic term u_i. Various auxiliary assumptions regarding the nature of this function will be imposed as various estimation methodologies are used and compared throughout this chapter.

The research objective of this chapter is focused primarily on the indicators of intertemporal discounting, so it is critical only that the explanatory variables other than the discounting variables appropriately act as control variables so that the relationships of interest can be accurately examined. One potential problem is that if there was a high degree of multicollinearity between the variables of interest and the other variables, as it would then be difficult to discern the effect of the discounting variables from the other controls. In Chapter 3 it was shown that the discounting indicators are not strongly associated with the other control variables, so multicollinearity is not likely to be a major concern. Major empirical concerns with estimations of models of complex lifestyle choices is the potential for endogeneity issues, and the problems of inference of causality, so these will be addressed in the following section.

4.2.3 Potential Endogeneity Issues and Causality

As a prelude to the discussion of potential endogeneity issues in the specified model, some brief comments should be made on the endogeneity issues that have been avoided by the exclusion of certain variables from the model. The reader may note that the explanatory variables in the empirical model do not include some of the variables most likely to be able to explain body weight outcomes: variables representing diet and exercise. Inclusion of these variables without appropriate mitigation techniques would certainly have resulted in a strong likelihood of endogeneity problems and biased estimates. The endogeneity problem could be caused by reverse causality, where body weight is an important determinant of the lifestyle choice, or by correlation of diet or exercise behaviour with an important unobserved variable. These technical estimation issues are avoided since these variables are not present.

It is not just technical reasons of estimation that resulted in the decision to exclude diet and exercise from the set of control variables. There is also a matter of interpretation of the estimates obtained from the model. If diet and exercise were included as control variables in the estimation, and appropriate techniques were used to handle the endogeneity issue, then the estimate of the association between discounting and body weight outcomes would be an estimated effect holding diet and exercise constant. This is not a very interesting estimate, since one would expect the effect of discounting on body weight to operate primarily *through* the diet and exercise choices, and these effects should be included in the total effect of discounting on body weight outcomes. A simultaneous equation approach may be useful to analyse these causal pathways, and this type of analysis is presented in Chapter 6. The derivation of a reduced form model of body weight determination from theory of course did not suggest the inclusion of diet and exercise variables. This shows the importance of carefully deriving a reduced form model in such a way, rather than simply including all the seemingly relevant explanators of the outcome of interest.

Not only diet and exercise but also other lifestyle variables that may be determinants of body weight outcomes should be excluded from the reduced form model due to the two reasons above of endogeneity and interpretation. Essentially the estimation approach attempts to control for the more stable individual characteristics of individuals, rather than the contemporaneous choices they make. There is some similarity here with the 'deep determinants' literature regarding economic growth (See Bhattacharyya 2004). In economic growth literature, it is recognised that capital and labour are the major proximate determinants of growth, but the 'deep determinants' literature investigates deeper factors that affect growth *through* their effects on capital and labour. Degree of intertemporal discounting is an individual trait that could affect many lifestyle choices that impact body weight, as such the question of interest is how discounting affects body weight, controlling for other individual traits, but allowing lifestyle choices to vary.

Although the reduced form model specification aims to include exogenous variables, there is still the possibility for some endogeneity of the included explanatory variables. Some individual characteristics, such as age and sex, can easily be assumed to be exogenous variables, while others are more debatable. Some research has purported to show evidence of an effect of body weight on income in certain subgroups (Baum II and Ford 2004, Han, Norton, and Stearns 2009), but others have found no evidence of such a relationship (Norton and Han 2008). In any case it does not seem likely that this effect would be as important as the well documented effect of income on body weight outcomes. Similarly, some have proposed that body weight could affect education rather than the other way around. Once again, since it seems highly likely that this reverse effect is negligible compared to the main effect of education on body weight, it will be assumed that this does not pose endogeneity problems. These assumptions are based in part on the evidence that was presented in the literature review in Chapter 2 of this thesis.

As was previously discussed in Chapter 2, authors such as Becker and Mulligan (1997) have suggest reverse causality of health on discounting, although no research has specifically applied this to body weight. This does not seem as plausible as the direction of causality from discounting to body weight outcomes. However it is unfortunately difficult to test for this reverse causality in the data. Throughout this thesis it will be assumed that this reverse causality is not a problem that will bias the estimation results. However, it will be recognised throughout that the potential for this problem leaves it appropriate to more conservatively interpret the estimation results as conditional associations between the variables, rather than estimates of causation.

Due to the potential for endogeneity problems with some of the variables, some might argue that the use of instrumental variables could be appropriate to rectify any such problems. This technique will not be used in this thesis. An instrumental variable must be appropriately correlated with the explanatory variable with the endogeneity problem, and not with the error term of the regression. This means an instrumental variable should not be correlated at all with body weight outcomes other than through the endogenous variable for which it instruments. Since the issue of body weight determination is so complex and not well understood, it does not seem likely to find any such appropriate instrumental variables. If instrumental variables are inappropriately applied they can lead to less accurate results than the original potentially biased estimates (Murray 2006).

Thus, since the 'deep determinants' approach reduces the problems of endogeneity, and the explanatory variables in the model seem unlikely to have endogeneity problems, are there are no appropriate instruments available to test these assumptions, it seems logical to leave the problem of endogeneity unaddressed in an empirical sense at risk of producing more fallacious results. Of course it is recognised that this approach does not fully resolve the potential issue of endogeneity, but it seems the logical way to proceed, while conservatively interpreting results as partial associations rather than evidence of causality.

It is common in epidemiology to refer to the 'risk factors' of a disease, which refer to variables associated with an increased risk of the disease. Risk factor models develop this idea further by estimating a model of the conditional associations of a set of variables with the outcome of interest, controlling for the other variables. It is recognised that risk factors are not necessarily causal, but they are still considered useful information with regard to categorising individuals at risk of the condition, and developing understanding of the determinants of the condition. The estimated models in this chapter should be interpreted in this way, as risk factor models. In particular a focus is on the potential role of intertemporal discounting as a *risk* *factor* for adverse body weight outcomes.

4.3 Data and Descriptive Statistics

4.3.1 Data Source

The data source for this analysis is the 2008 South Australian Health Omnibus Survey (SAHOS). The SAHOS is a survey that has been conducted annually since 1991 through interviews with a sample of South Australians. It is a randomly drawn representative sample of South Australians aged 15 and over. Further details of the survey methodology have been published elsewhere (Wilson, Wakefield, and Taylor 1992). Observations that had missing values on any of the utilized variables were excluded, bringing the sample used for the following empirical work to 1868 observations, the same sample analysed in Chapters 3 and 5.

4.3.2 Body Mass Index

The Body Mass Index (BMI) is defined as:

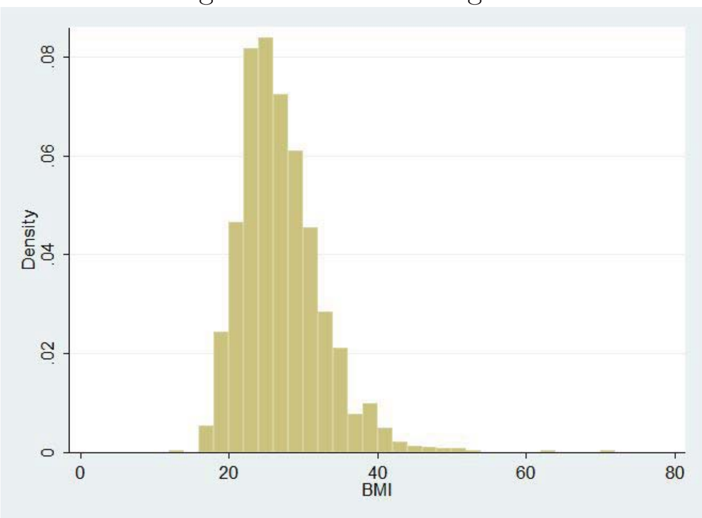
$$\text{BMI} = \frac{\text{weight(kg)}}{[\text{height(m)}]^2}$$

A BMI variable was created using self-reported measures of height (in either centimetres or feet and inches), and weight (in either kilograms or stones and pounds). The number of respondents in each of the usual BMI categories are shown in Table 4.1. These figures are very similar to the usual prevalence figures, that were discussed in Chapter 2. The Australian National Health Survey 2007-2008 found that 25% of adults were obese, and 37% of

Table 4.1: BMI Categories in Sample

	Definition	Count	Percentage	Cumulative
Underweight	BMI < 18.5	36	1.93%	1.93%
Normal weight	$18.5 \leq BMI < 25$	708	37.90%	39.83%
Overweight	$25 \leq BMI < 30$	659	35.28%	75.11%
Obese	BMI ≥ 30	465	24.89%	100%

Figure 4.1: BMI Histogram



adults were in the overweight (but not obese) range (ABS 2009a). Figure 4.1 shows a histogram of the BMI distribution in the sample used in this chapter. The fact that health variables such as BMI have been elicited by self-report measures introduces potential bias due to mis-reporting, however this is not expected to have a large impact. Previous studies have shown that self-report BMI data does not introduce a large bias (Burkhauser and Cawley 2008).

4.3.3 Explanatory and Control Variables

The explanatory variables of interest are the measures of intertemporal discounting discussed and analysed in some detail in Chapter 3. Four variables were discussed in that chapter: estimated discount rates elicited in the monetary and health domains, and binary indicator variables representing the presence of positive discounting in each of those same two domains. Due to the highest proportions of individuals being either in the non-positive discounting range, or the discount rate range between 0 and 0.05, and very small numbers of respondents in some of the other elicited discount rate ranges, much of the elicited variation in discount rates can be captured simply with the binary indicator variables. As such, the measures of intertemporal discounting used as explanatory variables in the analysis presented here will be the binary indicator variables PDR-M and PDR-H, representing positive discount rates in the monetary and health domains respectively.[2]

The other variables that will be used as per the vector of explanatory variables derived in Section 4.2.2 are age, sex, income, education, and functional health literacy. The majority of the variables are quite self explanatory, with brief descriptions in Table 4.2. The exception is the functional health literacy variable, which requires a more formal introduction.

A series of questions in the SAHOS were asked to generate a relatively new measure of functional health literacy known as the 'Newest Vital Sign'

[2]Similar analysis was undertaken using the elicited of discount rates. The qualitative nature of the results is similar, with a slightly reduced effect magnitude for the discounting variables.

Table 4.2: Variable Descriptions

Variable	Description
BMI	Respondent's BMI; BMI = $\frac{\text{weight(kg)}}{\text{height}^2(\text{m}^2)}$
PDR-M	Indicator of positive discounting in the monetary domain
PDR-H	Indicator of positive discounting in the health domain
Age	Respondent's age in years
Age Squared	Respondent's age in years, squared
Female	Binary variable, =1 for females
Education Variables	
Certificate/Diploma (>1FTE)	
Certificate/Diploma ($\leq$1FTE)	
Trade/Apprenticeship	
Left school after 15, still studying	A set of binary variable indicating the respondent's highest qualification. The base group is 'bachelor degree or higher'
Left school after 15	
Left school at 15 or less	
Still at school	
Income Variables	
\$80001-\$100000	
\$60001-\$80000	
\$50001-\$60000	
\$40001-\$50000	A set of binary variable indicating the respondent's household income range. The base group is '$\geq$ \$100000'
\$30001-\$40000	
\$20001-\$30000	
\$12001-\$20000	
$\leq$ \$12000	
Functional Health Literacy	
At Risk	A set of binary variable indicating the respondent's categorization according to the 'Newest Vital Sign'. The base group is 'Adequate'
Inadequate	

(NVS). The NVS is based on six questions regarding a nutrition label for ice-cream, and is designed as a short survey measure that captures much of the variation in health literacy measured by the more in-depth 'Test of Functional Health Literacy in Adults' (TOFHLA) (Parker et al. 1995). Possible NVS categorizations from lowest to highest functional health literacy are inadequate, at-risk and adequate. The main benefit of the NVS against its rivals is its short length; it only takes about 3 minutes to complete on average (Johnson and Weiss 2008). It is also particularly relevant in the context of body weight, since the questions are related to diet.

The psychometric properties of the NVS have been investigated in a validation study and showed good internal consistency, good criterion validity (taking the TOFHLA as the relevant criterion) and good sensitivity (Weiss et al. 2005). A further analysis of the NVS by Osborn et al. (2007) found only a moderate correlation with the Rapid Estimate of Adult Literacy in Medicine (REALM), but a relatively high correlation with the shortened S-TOFHLA, and once again high internal consistency and high sensitivity for detecting limited literacy. This second analysis found no statistically significant relationships between the NVS and several other measures of health knowledge and health status, while the S-TOFHLA has some significant results, however this does not suggest that the NVS is not useful, since the non-significant results may have been driven by small sample size and several methodological issues.

As a relatively new measure, which was originally intended as a quick measure of functional health literacy to be used in primary care, the majority of the research today on the NVS focuses on validating it for that use. However, as it has been shown to be closely related to the more commonly used TOFHLA and S-TOFHLA, its use in research can be usefully compared to studies that have used those.

4.3.4 Preliminary Variable Associations

Table 4.3 shows the interquantile means of each of the variables used in this analysis. That is, it shows the mean and standard deviation of each variable for each of the subsamples defined by the deciles of BMI. This gives an indication of how the characteristics of individuals change along the distribution of BMI. It is useful to remember from Table 4.1 that the change from the underweight to normal weight occurs at the 1.93th percentile of BMI, followed by overweight status at the 39.83th percentile, and obese status at the 75.11th percentile.

It is interesting to note that the proportion of individuals with a positive rate of intertemporal discounting in the monetary domain is noticeably higher in the upper quantiles that correspond approximately to the 'obese' range. On the other hand, there is little difference in the proportion of individuals with a positive discount rate in the health domain across the quantiles of BMI. It appears that the unconditional association between discounting and body weight is stronger for the monetary domain indicator than the health domain indicator.

The key focus of this paper is the potential effect of intertemporal discounting on body mass index outcomes, so rather than how discounting

Table 4.3: Inter-Quantile Means

	Full Sample	0-0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1
BMI	27.041	19.44	21.86	23.22	24.43	25.62	26.88	28.31	29.97	32.33	38.45
PDR-M	.191	.166	.150	.197	.151	.202	.182	.173	.160	.283	.242
PDR-H	.103	.075	.112	.122	.091	.133	.112	.097	.086	.107	.097
Age	49.50	41.98	47.66	50.09	51.49	49.64	50.51	51.84	50.44	50.44	50.92
Female	.549	.743	.588	.559	.527	.447	.465	.454	.503	.588	.613
Bachelor degree or higher	.203	.273	.273	.234	.231	.213	.203	.200	.139	.150	.118
Certificate/Diploma (>1FTE)	.146	.112	.107	.176	.113	.186	.150	.134	.160	.187	.129
Certificate/Diploma ($\leq$1FTE)	.122	.123	.096	.133	.172	.117	.102	.108	.118	.118	.129
Trade/Apprenticeship	.131	.091	.091	.078	.081	.138	.187	.178	.193	.128	.140
Left school after 15, still studying	.036	.037	.053	.032	.022	.037	.027	.027	.043	.037	.043
Left school after 15	.230	.235	.251	.213	.231	.131	.198	.216	.219	.246	.296
Left school at 15 or less	.118	.070	.107	.122	.140	.112	.123	.119	.123	.134	.134
Still at school	.015	.059	.021	.011	.011	.005	.011	.016	.005	.000	.011
$\geq$ $100000	.198	.257	.176	.212	.204	.239	.193	.189	.267	.144	.097
$80001-$100000	.112	.107	.123	.122	.108	.138	.070	.108	.118	.123	.108
$60001-$80000	.141	.102	.155	.144	.113	.138	.187	.146	.112	.122	.194
$50001-$60000	.085	.096	.118	.053	.086	.074	.096	.108	.070	.112	.038
$40001-$50000	.084	.096	.080	.090	.097	.059	.096	.076	.080	.075	.091
$30001-$40000	.085	.075	.075	.106	.081	.059	.107	.103	.064	.080	.097
$20001-$30000	.124	.123	.118	.122	.129	.117	.086	.124	.139	.150	.129
$12001-$20000	.124	.096	.128	.090	.140	.106	.118	.130	.102	.134	.194
$\leq$ $12000	.047	.048	.027	.059	.043	.069	.048	.016	.048	.059	.054
Adequate (NVS)	.592	.631	.583	.559	.613	.612	.626	.573	.615	.529	.581
At Risk (NVS)	.230	.230	.251	.266	.215	.239	.193	.238	.198	.246	.220
Inadequate (NVS)	.178	.139	.166	.176	.172	.149	.181	.189	.187	.225	.199

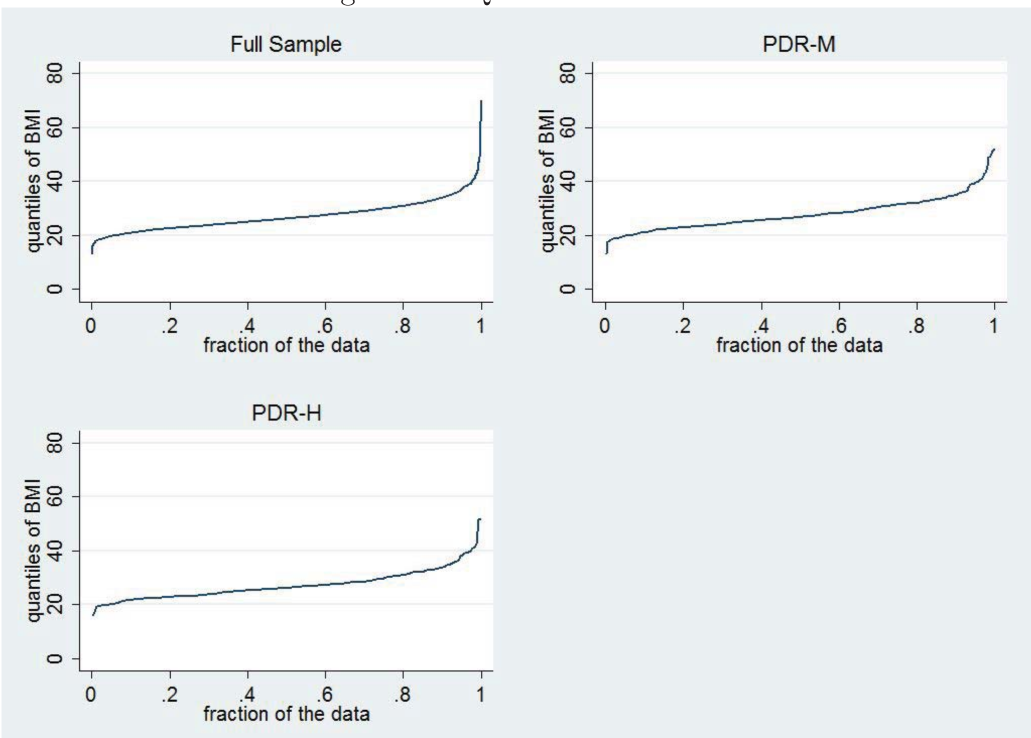
varies with body weight, perhaps more important is how body weight varies with discounting. 31% of those respondents with a positive monetary discount rate are obese, compared to only 23% for the rest of the sample (F=10.19;p=0.0014). On the other hand, if the sample is separated based on the health domain indicator of a positive discount rate, both subsamples have a prevalence of obesity of 25% (F=0.00;p=0.9939).

Similarly, comparing the discounting and non-discounting subsamples for general overweight status (including obese status), it is found that using the monetary indicator 65% of discounters are overweight, versus 59% of non-discounters (F=5.12;p=0.0237). And using the health domain indicator, 61% of discounters are overweight, compared to 60% of non-discounters (F=0.08;p=0.7718).

Already two trends are noticeable. Firstly, the monetary domain indicator of intertemporal discounting shows evidence of being associated with BMI outcomes, whereas the health domain indicator does not. Secondly, the association between the monetary domain indicator of intertemporal discounting and BMI seems stronger for those in the obese category than those in the overweight category.

Since there is reason to believe the effect of intertemporal discounting on weight outcomes may vary across the distribution of weight, Figure 4.2 shows the unconditional quantile distribution of BMI, alongside the quantile distributions of BMI conditioning separately on an positive discount rate elicited in each domain. From examination of these distributions of quantiles it can be seen that conditioning on a positive level of intertemporal discounting (that

Figure 4.2: Quantiles of BMI



is, looking at people who are more impatient), the distribution of quantiles has a relatively similar shape to the unconditional distribution. However, there is a subtle difference in the upper-quantiles. For both conditional distributions, BMI seems to be higher at the upper quantiles.

For example, where the notation Q_{95} represents the 95th percentile:

$Q_{95}(\text{BMI}) = 37.21$

$Q_{95}(\text{BMI}|\text{PDR-M=1}) = 39.61$

$Q_{95}(\text{BMI}|\text{PDR-H=1}) = 38.32$

The conditional distributions in Figure 4.2 each condition on only one variable, so perhaps do not have a very useful interpretation. It may be that the differing distributions of BMI are due to other variables that are correlated with intertemporal discounting. To better analyse the conditional distributions multivariate techniques must be used.

4.4 Multivariate Analysis

4.4.1 Multivariate Linear Regression Estimation

Table 4.4 reports linear regression (OLS) estimates of the vector of explanatory variables defined previously on BMI as the dependent variable. The main specification in column (1) is the set of results of primary interest. These will be discussed first, before moving on to some alternate specifications also presented in the same table.

A reader who is not familiar with the literature that estimates similar models may feel that the fit of the model, as represented by the R^2 value, is

Table 4.4: Multivariate Linear Regression Coefficient Estimates

Dependent Variable:BMI	(1) Main Specification	(2) Underweight Excluded	(3) Variable Exclusions
PDR-M	1.120***	1.076***	1.100***
	(0.346)	(0.345)	(0.346)
PDR-H	-0.255	-0.315	
	(0.424)	(0.419)	
Age	0.328***	0.308***	0.327***
	(0.0423)	(0.0418)	(0.0418)
Age Squared	-0.00308***	-0.00294***	-0.00307***
	(0.000419)	(0.000412)	(0.000408)
Female	-0.208	-0.138	-0.206
	(0.264)	(0.262)	(0.262)
Highest Qualification			
Bachelor degree or higher		(Base Group)	
Certificate/Diploma (>1FTE)	1.134***	1.249***	1.120***
	(0.413)	(0.407)	(0.413)
Certificate/Diploma ($\leq$1FTE)	1.002**	1.021**	0.976**
	(0.452)	(0.447)	(0.454)
Trade/Apprenticeship	1.850***	1.829***	1.868***
	(0.449)	(0.446)	(0.452)
Left school after 15, still studying	1.827**	1.891**	1.804**
	(0.795)	(0.793)	(0.795)
Left school after 15	1.213***	1.202***	1.195***
	(0.401)	(0.400)	(0.397)
Left school at 15 or less	1.440***	1.528***	1.451***
	(0.555)	(0.552)	(0.548)
Still at school	-0.0940	0.298	-0.0950
	(0.910)	(0.940)	(0.908)
Household Income Range			
$\geq$ \$100000		(Base Group)	
\$80001-\$100000	0.743*	0.683	0.712*
	(0.421)	(0.420)	(0.418)
\$60001-\$80000	1.098**	1.151***	1.066**
	(0.443)	(0.440)	(0.439)
\$50001-\$60000	0.192	0.197	0.164
	(0.464)	(0.460)	(0.462)
\$40001-\$50000	0.586	0.676	0.561
	(0.559)	(0.554)	(0.558)
\$30001-\$40000	0.797	0.729	0.771
	(0.508)	(0.506)	(0.502)
\$20001-\$30000	0.751	0.832*	0.723
	(0.495)	(0.491)	(0.490)
\$12001-\$20000	1.576***	1.529***	1.572***
	(0.531)	(0.522)	(0.535)
$\leq$ \$12000	0.784	0.969	0.788
	(0.730)	(0.716)	(0.728)
Functional Health Literacy			
Adequate		(Base Group)	
At Risk	-0.223	-0.0565	
	(0.332)	(0.328)	
Inadequate	0.192	0.267	
	(0.398)	(0.395)	
Constant	17.49***	18.09***	17.47***
	(1.071)	(1.063)	(1.061)
Observations	1868	1832	1868
R-squared	0.065	0.060	0.064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

quite low. However this R^2 value is in fact quite similar to those found in similar analyses of body weight outcomes. Ikeda, Kang, and Ohtake (2010) find R^2 between 0.021 and 0.094 for their model specifications most similar to those presented here, which include discounting variables and demographics as explanatory variables for BMI. These levels of R^2 values are not specific to the literature on discounting, with many other estimated models of body weight having similar values, as reviewed previously in Section 2.6 of this thesis. The low R^2 values obtained in these studies are not indicative of poor models, but rather indicate the amount of *unobservable* variation in the biology and psychology of individuals that is relevant to their body weight outcome.

According to the main specification estimate in Table 4.4, the statistically significant point estimate of the effect of the PDR-M variable on BMI is 1.120. This means that an individual who showed evidence of a positive discount rate in the monetary domain, according to the stated-preference questions used, will on average have a BMI 1.12 index units higher, all other variables held constant. This would correspond for example to an increased weight by 3.24kg for an individual with a height of 170cm.

On the other hand, the variable that indicates a positive rate of intertemporal discounting in the health domain is not statistically significantly different from zero in this specification. This variable may not be associated with body weight outcomes at all.

The estimated coefficients on the age variables are significant, showing a positive but decreasing effect of age on body weight[3]. Several of the education and income variables are significant and positive, indicating a positive effect of being in those groups on BMI relative to the high education and high income base groups. The coefficients on the functional health literacy variables are not significantly different from zero, suggesting perhaps that the other demographic variables sufficiently control for this characteristic.

Specification (3) titled 'Variable Exclusions' shows the estimation results of the same models, with the exclusion of the variables representing discounting in the health domain, and functional health literacy. These particular variables were excluded since their presence in the model is more tenuous than the other demographic variables are they were not found to bes significant. The estimation results of this specification are not dissimilar to the main specification. So if these variables in fact should not be included in the model, but are erroneously included, this does not seem to bias the estimates on the other variables noticeably. This gives further confidence in the model specifications including these variables, including models in later sections.

As has been discussed previously, there may be differences in the effect of various explanatory variables over the distribution of BMI. In particular, some explanatory variables may move BMI towards healthy levels, and thus have a positive effect for underweight individuals and a negative effect for overweight individuals. To see if the small number of underweight individuals is biasing the results, column (2) shows estimates of the main specification

[3]The estimated marginal effect of age on weight would become negative for ages above 106 years, which is outside the age range of the sample

with the only difference being the exclusion of all underweight individuals from the sample of analysis. This does not greatly change the estimates and qualitative results, but perhaps the small changes are actually quite surprising considering the sample has simply lost 36 of a total 1868 observations. This shows some evidence of the differing effect of explanatory variables on body weight across the BMI distribution, which should be investigated further.

4.4.2 Probit Estimation

When looking at body weight outcomes, a different approach to estimating the effect of explanatory variables on BMI, is to estimate the effect of the variables on the probability of being in a particular weight category. Estimating the effect of variables on the probability of being obese or overweight is a common topic of interest. This question is quite different in nature, however the body weight outcome of presence in a particular weight range will depend on the same vector of explanatory variables as BMI outcome depended on. In this section probit models will be used to estimate models of the probability of obese status, and overweight status[4].

The probit model can be represented through a latent variable approach. A binary variable that is the outcome of interest, say being obese, is denoted by y, taking the value '1' if the individual is obese and '0' otherwise. A continuous latent variable y^* is defined, such that $y = 1$ if and only if $y^* > 0$. The latent variable y^* is assumed to depend linearly on a vector of

[4]Logit specifications produce quite similar results, and so are not presented here.

Table 4.5: Probit Regression Estimates

Dependent Variable	(1) Obese (Coefficient)	(2) Obese (Marginal Effect)	(3) Overweight (Coefficient)	(4) Overweight (Marginal Effect)
PDR-M	0.236***	0.0764***	0.196**	0.0741**
	(0.0817)	(0.0277)	(0.0791)	(0.0292)
PDR-H	-0.0548	-0.0167	-0.0349	-0.0135
	(0.108)	(0.0323)	(0.100)	(0.0389)
Age	0.0671***	0.0208***	0.0622***	0.0239***
	(0.0123)	(0.00377)	(0.0104)	(0.00400)
Age Squared	-0.000670***	-0.000207***	-0.000572***	-0.000220***
	(0.000122)	(3.74e-05)	(0.000104)	(3.99e-05)
Female	0.132*	0.0407*	-0.202***	-0.0772***
	(0.0691)	(0.0211)	(0.0631)	(0.0240)
Highest Qualification				
Bachelor degree or higher		(Base Group)		
Certificate/Diploma (>1FTE)	0.379***	0.128***	0.374***	0.137***
	(0.118)	(0.0422)	(0.105)	(0.0359)
Certificate/Diploma ($\leq$1FTE)	0.219*	0.0715*	0.196*	0.0736*
	(0.124)	(0.0424)	(0.110)	(0.0402)
Trade/Apprenticeship	0.379***	0.128***	0.573***	0.202***
	(0.125)	(0.0449)	(0.113)	(0.0351)
Left school after 15, still studying	0.438**	0.153**	0.378**	0.136**
	(0.184)	(0.0696)	(0.173)	(0.0570)
Left school after 15	0.346***	0.114***	0.254***	0.0956***
	(0.109)	(0.0376)	(0.0972)	(0.0355)
Left school at 15 or less	0.343**	0.115**	0.337***	0.124***
	(0.134)	(0.0481)	(0.125)	(0.0432)
Still at school	-0.123	-0.0363	-0.0272	-0.0105
	(0.385)	(0.109)	(0.273)	(0.106)
Household Income Range				
$\geq$ \$100000		(Base Group)		
\$80001-\$100000	0.292**	0.0970**	0.0254	0.00976
	(0.122)	(0.0430)	(0.111)	(0.0426)
\$60001-\$80000	0.168	0.0541	0.112	0.0424
	(0.119)	(0.0397)	(0.107)	(0.0400)
\$50001-\$60000	0.0812	0.0257	-0.0279	-0.0108
	(0.140)	(0.0454)	(0.123)	(0.0476)
\$40001-\$50000	0.167	0.0542	-0.118	-0.0461
	(0.141)	(0.0478)	(0.128)	(0.0501)
\$30001-\$40000	0.163	0.0528	-0.0258	-0.00996
	(0.141)	(0.0475)	(0.130)	(0.0503)
\$20001-\$30000	0.307**	0.102**	-0.0484	-0.0187
	(0.133)	(0.0470)	(0.122)	(0.0475)
\$12001-\$20000	0.418***	0.142***	0.116	0.0441
	(0.135)	(0.0495)	(0.130)	(0.0485)
$\leq$ \$12000	0.402**	0.138**	0.0410	0.0157
	(0.179)	(0.0669)	(0.171)	(0.0652)
Functional Health Literacy				
Adequate		(Base Group)		
At Risk (NVS)	0.0274	0.00852	-0.0732	-0.0283
	(0.0835)	(0.0261)	(0.0787)	(0.0306)
Inadequate (NVS)	0.121	0.0385	0.0163	0.00626
	(0.0983)	(0.0320)	(0.0966)	(0.0371)
Constant	-2.805***		-1.428***	
	(0.312)		(0.262)	
Observations	1868	1868	1868	1868

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

explanatory variables x, with an error term u that is assumed to follow the conditional distribution $u|x \sim N(0, 1)$.

$$y^* = x\beta + u \tag{4.10}$$

Table 4.5 shows the estimated results of two probit regressions. Column (1) shows the estimated effects of each explanatory variable on the latent variable for obesity, in other words the β coefficients. Column (2) shows the marginal effect of each explanatory variable on the estimated probability of obesity, based on the same regression as Column (1). The marginal effects are calculated as the change in the estimated probability of being obese for a change from '0' to '1' for binary explanatory variables; and as the partial derivative of the estimated probability with respect to the explanatory variable for continuous explanatory variables. Columns (3) and (4) similarly show the estimated coefficients and marginal effects on the probability of being 'overweight' (which in this case as defined as inclusive of obesity).

The main point of interest is the estimated effect of the discounting variables on the probabilities of being obese or overweight. According to the estimate in Column (2), the marginal effect of PDR-M on the probability of obesity is 0.0764, which means that an individual who showed a positive discount rate in the monetary domain is 7.64% more likely to be obese all else constant according to the point estimate. Once again the health domain indicator of intertemporal discounting is not signficantly different from zero. The estimated marginal effects for the probability of being overweight are very similar to the obesity regressions for the discounting variables, with monetary discounting estimated to lead to a 7.41% increase in the probability of being overweight, and the health domain indicator not statistically signficant.

4.5 Quantile Regression Analysis

4.5.1 Methodology

Standard regression techniques such as Ordinary Least Squares estimate the effect of explanatory variables on the conditional mean of the dependent variable. Where measures of relative body weight such as BMI are concerned this may not be appropriate, since many variables could have different effects on various parts of the conditional distribution of BMI. For example the explanatory variable 'income' is suggested by some theories to have a positive impact on the weight of those who are underweight, and a negative impact on the weight of the overweight. Looking only at the effect of income on *mean* BMI not only obscures these varying effects, but may lead to the erroneous inference that the estimated effect is constant along the BMI distribution. In the previous section several techniques were considered that allowed in some restricted way the effect on body weight outcome to differ amongst various subgroups of individuals. However the categories of 'overweight' and 'obese' have somewhat arbitrary cut-offs, so a technique that allowed for different effects along the distribution of BMI more broadly seems more applicable.

Quantile Regression is a technique that is used here to estimate the effects of explanatory variables on different parts of the conditional BMI distribution, by estimating differing marginal effects at various conditional quantiles. The modern techniques of quantile regression were introduced by Koenker and Bassett (1978)[5]. Although this methodology has been around for several decades, and seems naturally applicable to estimations regarding weight outcomes, it is only in very recent times that the technique has come to gain popularity in this area. Studies that have used quantile regression to estimate models of BMI include Kan and Tsai (2004), Terry, Wei, and Esserman (2007a), Meltzer and Chen (2009) and Sassi, Devaux, Cecchini, and Rusticelli (2009).

Beyerlein, Fahrmeir, Mansmann, and Toschke (2008) compare various estimation methodologies in the estimation of risk factor effects on BMI, and conclude that quantile regression is one of the better methodologies. The appropriateness of using quantile regression to study BMI is also discussed in Gillman and Kleinman (2007), and Terry, Wei, and Esserman (2007b).

First, a brief review of what a 'quantile' actually is. For a real-valued random variable Y, with Cumulative Distribution Function $F(y) = Pr(Y \leq y)$, the τ-th quantile of Y for $\tau \in (0, 1)$ is defined as $Q_\tau(Y) = \inf\{y|F(y) \geq \tau\}$. For example, the median of a random variable Y is also called the 0.5-th quantile, $Q_{0.5}(Y)$.

If there is a sample (y_i, x_i), where i denotes an observation, and x is a vector of regressors, then it is possible to estimate the quantiles of y, conditional on the regressors x. Assuming that the conditional quantile function

[5] For further reading see Buchinsky (1998), Koenker and Hallock (2001), Yu, Lu, and Stander (2003), and Koenker (2005)

has a linear form[6], it can be expressed as:

$$Q_\tau(y_i|x_i) = x_i'\beta_\tau \tag{4.11}$$

$$y_i = x_i'\beta_\tau + u_{\theta_i} \tag{4.12}$$

$\hat{\beta}_\tau$, the estimator of β_τ, solves:

$$\min_\beta \frac{1}{n}\{\sum_{i:y_i \geq x_i'\beta} \tau|y_i - x_i'\beta| + \sum_{i:y_i < x_i'\beta}(1-\tau)|y_i - x_i'\beta|\} \tag{4.13}$$

That is, the estimates of $\hat{\beta}_\tau$ are estimated using weighted absolute deviations. Note in the notation that the $\hat{\beta}_\tau$ is denoted with a τ to signify that its values can vary across different quantiles, unlike in the standard regression models. This optimization problem is not differentiable, and so it cannot be solved using gradient optimization methods and is instead solved using linear programming methods.

The above definitions, expressed in a more general form for ease of exposition, are used in this paper in the quantile regression estimates by taking y_i to be body mass index, and the vector x_i to be the set of regressors derived in Section 4.2.2.

In the estimation results subsequently presented, the quantile regression estimates have been obtained using the *sqreg* command in the program Stata 10 (StataCorp 2007). This procedure simultaneously estimates regressions at each of the quantiles, with a 0.05 step between each quantile, and uses

[6]This assumption is not crucial. Like OLS estimates, which can be interpreted simply as best linear estimates of the conditional expectation function if the model is specified as linear when it is not, quantile regression estimates can similarly be usefully interpreted as a linear approximation of the true conditional quantile function (Angrist, Chernozhukov, and Fernndez-Val 2006)

a bootstrapping approach to derive standard errors which allows for potential heteroskedasticity of the errors. The bootstrapping approach used 400 repetitions.

4.5.2 Results

The quantile regression estimates of the vector of explanatory variables used throughout this chapter on BMI are shown in Figures 4.3 to 4.5, and the same results presented in a different format in Table 4.6.

The figures show the the results as point estimates of the quantile regression coefficients for each regressor of their marginal effect on each conditional quantile (the $\hat{\beta}_\tau$'s) with a solid line. The plots are based on estimates at each 0.05 increment between the 0.05 and 0.95 quantiles, and include 90% confidence intervals based on bootstrap standard errors with 400 repetitions. The dotted lines show the OLS linear regression estimate and its confidence interval, as a comparator. Note that statistical significance at a particular quantile is given by the solid line at 0.00 being outside the confidence band. The tabulated results in Table 4.6 present estimates only for the 9 quantiles that are 0.10 quantile steps apart, however this is only for ease of exposition on a single page, and these estimates are in fact based on the the same simultaneous estimation process including a larger number of quantiles that is used for the figures.

The main variables of interest are shown in Figure 4.3. Here it can be seen that the monetary domain indicator (PDR-M) has a positive association with BMI that is statistically significant at most of the quantiles. The point

Figure 4.3: Quantile Regression Estimation Results (Discounting Indicators)

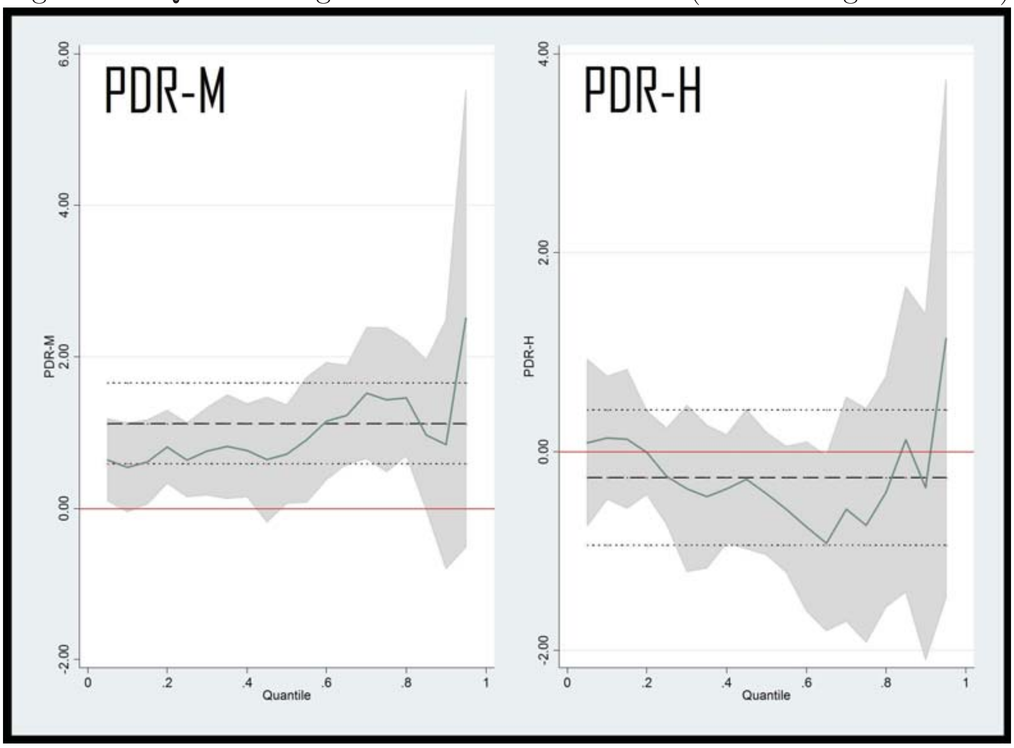


Figure 4.4: Quantile Regression Estimation Results (Continued)

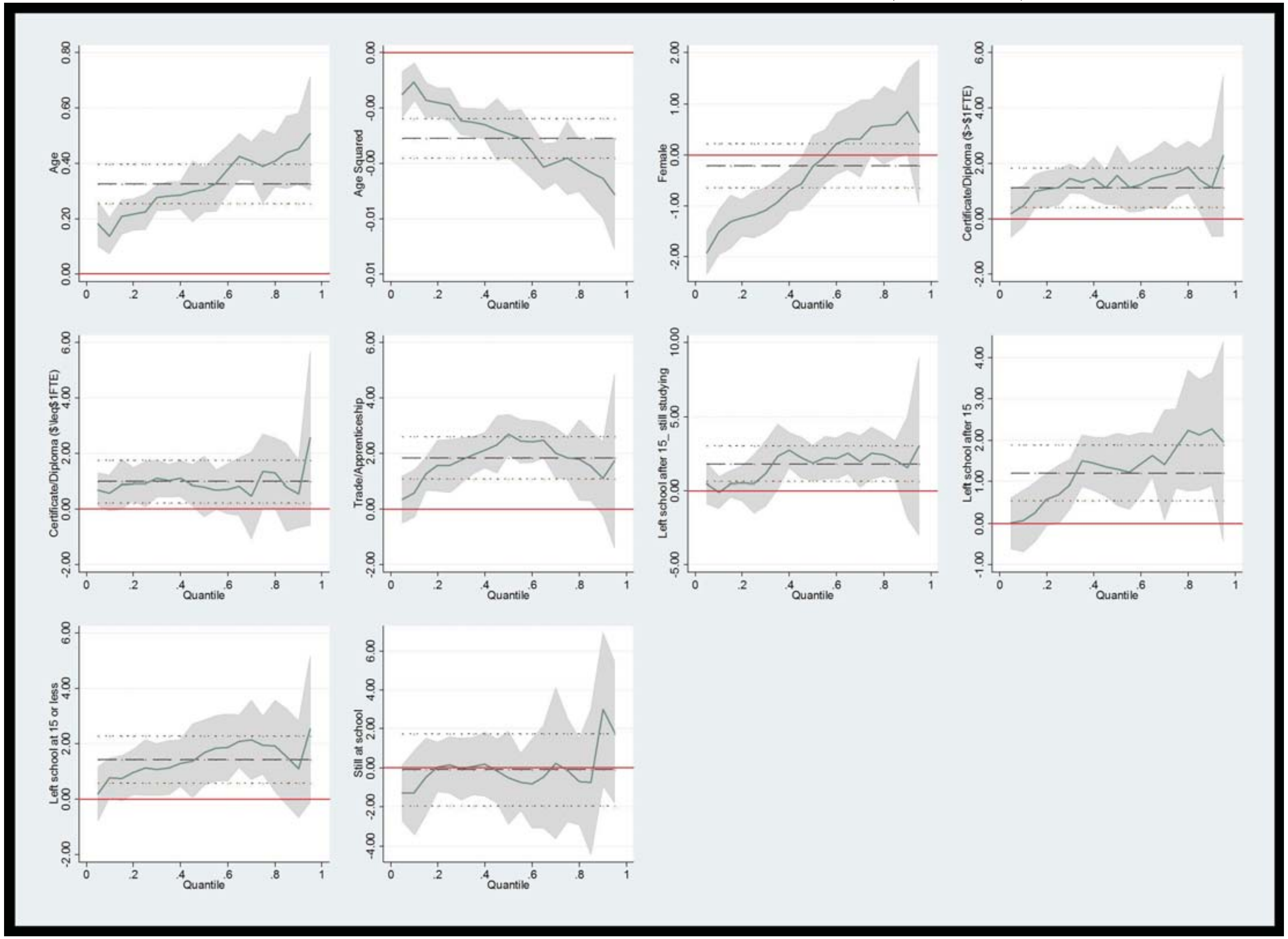


Figure 4.5: Quantile Regression Estimation Results (Continued)

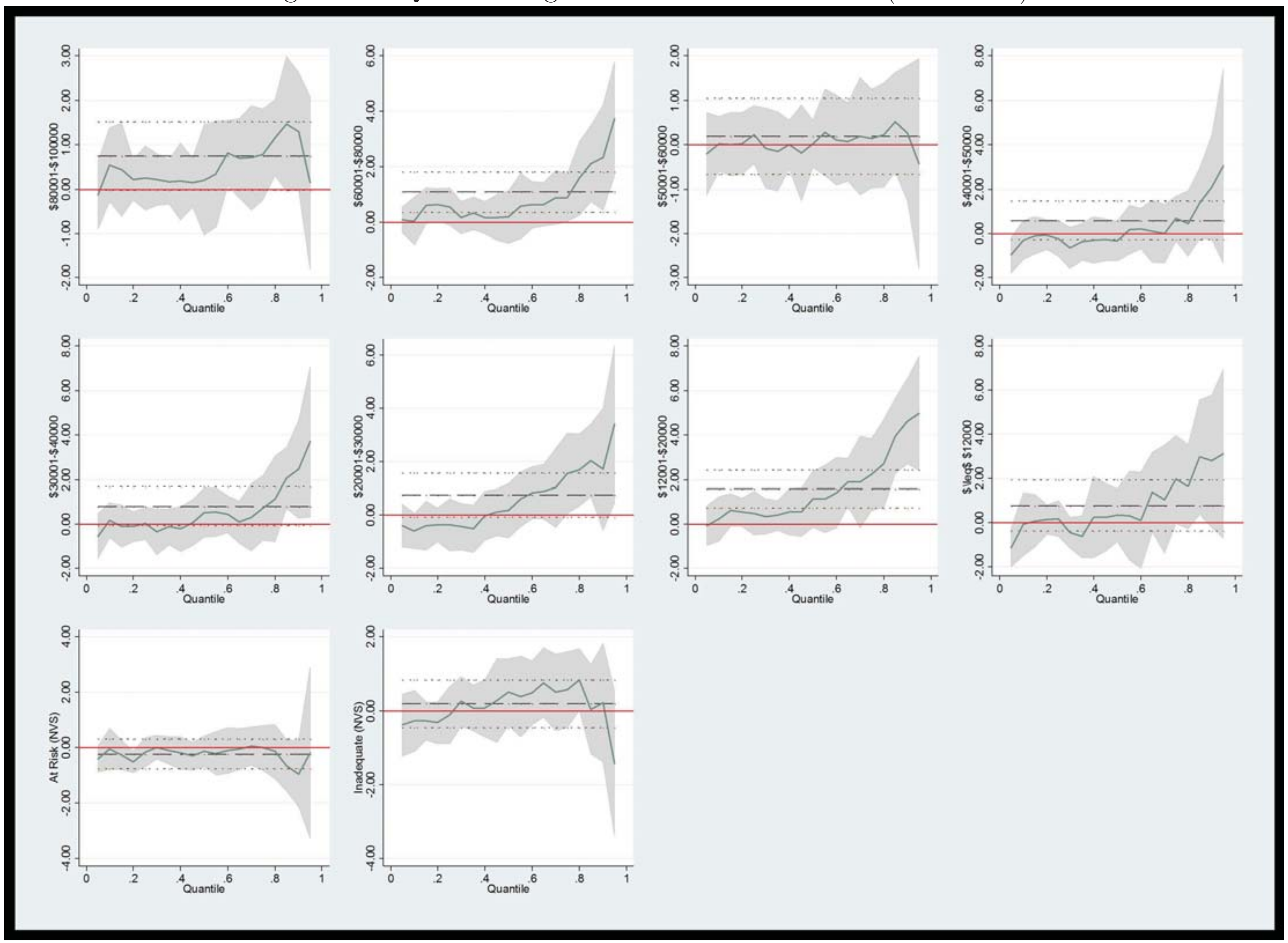


Table 4.6: Quantile Regression Estimates

Dependent Variable:BMI	(1) $Q_{0.1}$	(2) $Q_{0.2}$	(3) $Q_{0.3}$	(4) $Q_{0.4}$	(5) $Q_{0.5}$	(6) $Q_{0.6}$	(7) $Q_{0.7}$	(8) $Q_{0.8}$	(9) $Q_{0.9}$
PDR-M	0.544	0.816***	0.755**	0.768**	0.716*	1.152**	1.524***	1.457***	0.842
	(0.357)	(0.292)	(0.310)	(0.328)	(0.399)	(0.484)	(0.530)	(0.529)	(0.753)
PDR-H	0.141	-0.00621	-0.369	-0.373	-0.419	-0.750	-0.574	-0.404	-0.359
	(0.461)	(0.343)	(0.389)	(0.450)	(0.442)	(0.515)	(0.676)	(0.791)	(1.131)
Age	0.139***	0.216***	0.276***	0.285***	0.304***	0.378***	0.408***	0.410***	0.454***
	(0.0458)	(0.0372)	(0.0427)	(0.0424)	(0.0497)	(0.0524)	(0.0615)	(0.0739)	(0.0938)
Age Squared	-0.00105**	-0.00179***	-0.00247***	-0.00259***	-0.00292***	-0.00359***	-0.00396***	-0.00408***	-0.00453***
	(0.000466)	(0.000369)	(0.000427)	(0.000437)	(0.000497)	(0.000543)	(0.000613)	(0.000731)	(0.000904)
Female	-1.511***	-1.232***	-1.087***	-0.699**	-0.232	0.217	0.315	0.574	0.851
	(0.297)	(0.260)	(0.265)	(0.285)	(0.350)	(0.368)	(0.428)	(0.451)	(0.563)
Certificate/Diploma (>1FTE)	0.470	1.071**	1.454***	1.463***	1.571***	1.250**	1.577**	1.861***	1.144
	(0.505)	(0.427)	(0.359)	(0.413)	(0.532)	(0.561)	(0.640)	(0.712)	(1.059)
Certificate/Diploma (≤1FTE)	0.585	0.903**	1.099***	1.105**	0.815	0.735	0.484	1.288*	0.557
	(0.474)	(0.410)	(0.387)	(0.437)	(0.568)	(0.583)	(0.737)	(0.725)	(1.148)
Trade/Apprenticeship	0.576	1.568***	1.752***	2.120***	2.685***	2.428***	2.013***	1.783**	1.102
	(0.579)	(0.426)	(0.438)	(0.476)	(0.531)	(0.493)	(0.522)	(0.705)	(0.924)
Left school after 15, still studying	-0.124	0.492	1.153	2.739***	1.842**	2.149**	1.966**	2.410**	1.562
	(0.768)	(0.757)	(1.269)	(0.947)	(0.884)	(0.879)	(0.952)	(1.176)	(1.762)
Left school after 15	0.0616	0.586	0.934**	1.441***	1.294**	1.425***	1.402**	2.241***	2.270**
	(0.437)	(0.356)	(0.422)	(0.405)	(0.504)	(0.466)	(0.593)	(0.809)	(0.889)
Left school at 15 or less	0.774	0.984**	1.082**	1.313**	1.678**	1.878***	2.150***	1.923**	1.097
	(0.544)	(0.456)	(0.469)	(0.577)	(0.679)	(0.683)	(0.769)	(0.785)	(1.127)
Still at school	-1.278	0.0487	-0.0598	0.187	-0.499	-0.818	0.242	-0.711	2.992
	(1.081)	(0.979)	(0.971)	(0.962)	(1.156)	(1.321)	(1.650)	(2.164)	(2.999)
$80001-$100000	0.547	0.210	0.208	0.175	0.204	0.818	0.707	1.157	1.301
	(0.516)	(0.437)	(0.461)	(0.473)	(0.542)	(0.598)	(0.622)	(0.718)	(0.815)
$60001-$80000	0.0440	0.649	0.170	0.176	0.192	0.626	0.895	1.589**	2.335*
	(0.547)	(0.442)	(0.424)	(0.399)	(0.558)	(0.484)	(0.568)	(0.786)	(1.200)
$50001-$60000	0.0136	0.0234	-0.0789	0.00452	0.0121	0.102	0.193	0.218	0.260
	(0.535)	(0.485)	(0.490)	(0.553)	(0.610)	(0.572)	(0.626)	(0.746)	(0.874)
$40001-$50000	-0.296	-0.0647	-0.656	-0.296	-0.346	0.218	-0.0162	0.449	2.077
	(0.592)	(0.482)	(0.551)	(0.572)	(0.675)	(0.660)	(0.783)	(1.000)	(1.461)
$30001-$40000	0.164	-0.119	-0.345	-0.220	0.508	0.447	0.314	1.122	2.477
	(0.502)	(0.507)	(0.499)	(0.554)	(0.697)	(0.557)	(0.727)	(0.943)	(1.583)
$20001-$30000	-0.590	-0.357	-0.425	-0.0169	0.169	0.839	1.032	1.703**	1.719
	(0.463)	(0.519)	(0.555)	(0.631)	(0.658)	(0.709)	(0.840)	(0.743)	(1.141)
$12001-$20000	0.237	0.541	0.355	0.533	1.120	1.405*	1.871**	2.717**	4.621***
	(0.555)	(0.454)	(0.518)	(0.573)	(0.730)	(0.787)	(0.843)	(1.085)	(1.117)
≤ $12000	-0.0563	0.143	-0.429	0.258	0.342	0.118	1.058	1.635	2.791
	(1.056)	(0.582)	(0.670)	(0.832)	(0.820)	(1.125)	(1.134)	(1.167)	(1.714)
At Risk (NVS)	-0.0429	-0.515	0.0256	-0.174	-0.131	-0.0946	0.0655	-0.132	-0.935
	(0.379)	(0.314)	(0.337)	(0.348)	(0.407)	(0.432)	(0.474)	(0.513)	(0.730)
Inadequate (NVS)	-0.265	-0.319	0.256	0.0748	0.505	0.494	0.506	0.846	0.224
	(0.444)	(0.386)	(0.429)	(0.471)	(0.550)	(0.505)	(0.508)	(0.562)	(0.907)
Constant	17.72***	16.79***	16.53***	17.01***	17.74***	16.66***	17.33***	18.51***	20.30***
	(1.153)	(0.902)	(1.060)	(1.069)	(1.231)	(1.264)	(1.514)	(1.818)	(2.232)
Observations	1868	1868	1868	1868	1868	1868	1868	1868	1868

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

estimate of the effect increases over the quantiles, and is more pronounced at the higher quantiles representing overweight and obese ranges[7]. Although the OLS estimate reports a similar magnitude to many of the quantiles, the OLS estimation procedure clearly hides the potential increasing importance of discounting at the upper quantiles of the conditional BMI distribution. For this variable, as well as many others, the confidence interval gets much larger at the highest quantiles and statistical significance is lost. The asymptotic precision of quantile regression estimates depends on the density of observations near the quantile regression of interest (Koenker 2005), so this pattern of the confidence interval is not surprising. The estimated effects of PDR-H on BMI are statistically insignificant at the quantiles presented, so once again it seems that stated preference indicators of discounting in the health domain are not a good explanator of body weight outcomes.

Table 4.7 shows the results of hypothesis tests of the equality of the quantile regression coefficient estimates across selected sets of quantiles for the key variable PDR-M. The pairs shown correspond somewhat to the BMI categories, and interesting tests of symmetry. There are no cases where there is sufficient evidence to reject the hypothesis of equality of the coefficients at the usual levels of statistical significance. So it cannot be said that there is statistical evidence of the upward trend that seems apparent in the coefficient estimates for PDR-M, or indeed any difference over the conditional quantiles.

The sex variable indicating 'female' has a negative association with BMI at the lower quantiles, but at higher quantiles this association is lost, and

[7]Recall that 'overweight' begins at $Q_{0.3983}$ and 'obese' begins at $Q_{0.7511}$

Table 4.7: Hypothesis Tests of Equality Across Quantiles (PDR-M)

Test	p-value
$\beta_{0.05} = \beta_{0.95}$	0.1884
$\beta_{0.05} = \beta_{0.75}$	0.1624
$\beta_{0.05} = \beta_{0.50}$	0.8655
$\beta_{0.05} = \beta_{0.40}$	0.7376
$\beta_{0.40} = \beta_{0.75}$	0.1798
$\beta_{0.25} = \beta_{0.75}$	0.1251
$\beta_{0.50} = \beta_{0.75}$	0.1145
$\beta_{0.05} = ... = \beta_{0.95}$	0.9162

indeed at some quantiles a positive association is found. This is congruent with the fact that the distribution of BMI among females is different to the distribution among males. In particular, many epidemiological surveys (see for example ABS 2009a) find that a higher proportion of males than females are in the 'overweight' category, but that the proportion of females that are obese is similar to the proportion of males. It should be noted that the quantile regression clearly is more appropriate than OLS for the analysis of this variable, since the OLS method finds no relationship between BMI and sex due to the opposing effects along the BMI distribution canceling each other out.

Similar to the OLS regression results, the indicators of functional health literacy do not come out as significant variables. The age variables again show a positive but decreasing relationship with BMI, and some of the education and income variables are significant while some are not. Since these are primarily used as control variables there will not be any detailed discussion of these estimated results and the differences between the quantile regression and OLS results, which the interested reader can find in the figures and table.

4.6 Discussion and Conclusion

Through various methodologies used throughout this chapter a consistent result has been the positive association between the indicator of intertemporal discounting in the monetary domain, and body weight outcomes. This evidence is in contrast to the previous study of Borghans and Golsteyn (2006) which did not find a statistically significant relationship between stated-preference discounting measures and BMI. However it is supported by the very recent results in Ikeda, Kang, and Ohtake (2010). Comparison of the results here with that study is somewhat hampered by the different approaches, but it seems that the results presented in this chapter are generally higher in magnitude. One of the most interesting results from the analysis in this chapter is the magnitude of the estimate of discounting as a risk factor for adverse body weight outcomes. Although the exact estimate differed depending on the model specification and estimation methodology, the estimated coefficient on the monetary discounting variable ranged between about half the magnitude and very close to the magnitude of the coefficients on the education and income variables. This shows evidence of the elicited discounting variable as an important risk factor for obesity and high body weight outcomes.

It is also shown here that the association between intertemporal discounting and BMI may be different at different quantiles of the conditional BMI distribution. In particular, the point-estimate of the association of discounting tends to increase at the higher quantiles that include the overweight and obese ranges. However tests of statistical significance of the difference across quantiles do not support the rejection of the hypothesis that there is no difference. This does not mean that there is conclusive evidence that there is no trend, since there is similarly insufficient evidence to reject the hypothesis of certain increasing trends.

If this proposed increasing effect was present it could suggest that intertemporal discounting behaviour is a more important determinant of body weight for those who are obese, or in the higher parts of the overweight spectrum, than those who are normal weight or just a little overweight. If this were the case it could be an important insight since the health problems of excess weight increase as BMI increases, so it is often those who are highly overweight who are sought to be targeted for body weight reducing interventions. This interesting idea should not be ignored.

Juxtaposed to these results, the indicator of intertemporal discounting in the health domain is not statistically significantly different from zero at any of the quantiles examined in the quantile regressions, or in any of the other regression analysis. This does not support the hypothesis derived from the theory, that indicators of higher discount rates should be positively associated with BMI. However, this supports previous findings (Chapman and Coups 1999), that stated preference indicators of intertemporal preference elicited in the health domain actually have *less* explanatory power for health behaviours than those elicited in the monetary domain. This might be because the questions that these variables are based on are too cognitively difficult for respondents, so do not capture the intended aspects of preferences. The reason for this difficulty is in part because the types of questions that need to be asked are not the sort of decisions that individuals are familiar with making in their day-to-day lives, unlike the monetary domain questions that can be constructed to closely resemble familiar choice patterns. Another possibility which should not be ruled out is that there could be issues with the particular question used to elicit discounting behaviour in the health domain in this study, and that using a different question may have produced different results.

This chapter has provided evidence of an association between stated preference indicators of intertemporal discounting and body weight outcomes that until very recently had not been shown in the literature. It also provided evidence that although there may be domain independence in elicited discounted rates in the monetary and health domains, it is in fact the more commonly used monetary domain measures that seem most appropriate to use in the analysis of health outcomes. Quantile regression analysis helped show that the association between discounting and BMI may be stronger for the obese, who are in any case a group of particular clinical relevance. The analysis in this chapter is still somewhat preliminary in nature due to the new and innovative nature of the work, and there are still other related issues that should be further analysed. One such issue that is missing from the analysis in this chapter and could be potentially important, smoking behaviour, will be analysed in more detail in the following chapter.

Chapter 5

Smoking, Intertemporal Discounting, and Obesity

5.1 Introduction

Smoking is a lifestyle choice that provides immediate pleasure, but increases the chance of adverse health outcomes in terms of both morbidity and mortality. There may be reason to believe that a higher rate of intertemporal discounting will lead to a greater probability of smoking or a higher amount of smoking, since future health costs will be discounted. However, due to the addictive nature of smoking, there are a variety of proposed models of smoking behaviour, and not all support this contention.

The proposed relationship between intertemporal discounting and smoking parallels the relationship between intertemporal discounting and body weight discussed in the previous chapter. In addition, there are other direct relationships between smoking and body weight outcomes, which suggests that these pair of health outcomes perhaps should be analysed in conjunction with one another. Those individuals with a high discount rate may be more likely to become overweight, but also more likely to smoke, and if they do smoke this will reduce their weight. Thus estimating the relationship of discounting with body weight outcomes without controlling for the effect of the mitigating factor of smoking, as in the analysis in Chapter 4, may lead to a downward bias in estimates of the association between discounting and body weight outcomes. This chapter continues to use the same data that was introduced in Chapter 3 to investigate this proposition.

The story in the above paragraph relies on assumptions which are first separately investigated. The first part of this chapter investigates the potential relationship between heterogeneity in individuals' intertemporal discount rates and smoking status, without considering body weight at all. Although this mirrors to some extent the analysis of Chapter 4 regarding body weight, there are a number of differences in the context of smoking. Some background information about smoking is briefly discussed, along with a brief treatment of how models of smoking behaviour differ from models of body weight determination, which is primarily in that the former tend to focus on concepts of addiction. For this reason some of the models that have been proposed in the literature are 'myopic' models in which individuals do not take consideration of future consequences, which may not necessarily predict the relationship between intertemporal discounting and smoking behaviour, making the tests of that hypothesis in this chapter all the more important.

Empirical analysis is undertaken based on the South Australian Health Omnibus Survey data previously introduced, to analyse the relationship between discounting and smoking behaviour. Particular attention is given to differences between current smokers, former smokers, and 'never smokers' (those who have never regularly smoked). The evidence supports the positive relationship between intertemporal discount rate and the probability of smoking suggested by forward-looking models of addictive behaviour, and provides evidence against models of perfectly myopic smokers. That other similar studies have not found significant results may be due to the way in which former smokers have been treated in the analysis.

Two main questions are addressed in the joint analysis of discounting, smoking and body weight. The first of these is whether controlling for smoking has an impact on the estimates of the effects of discounting on body weight. As expected, it is found that there is a higher estimated association between discounting and body weight for non-smokers than for smokers, and thus that not controlling for this may have reduced the estimated coefficients in Chapter 4. This effect is found using a variety of econonometric techniques, so seems a robust result in the data.

Although there are many reasons to expect a direct negative effect of smoking on body weight, many epidemiological studies have not found this expected association. It has been suggested by Robb, Huston, and Finke (2008) that intertemporal discounting may have a mitigating effect on the estimates of the relationship between smoking and body weight. Since this is closely related to the analysis of this chapter, a section is devoted to this related question in the literature. The results found here support the previous results, and also add the important suggestion that the negative effect of smoking on body weight occurs primarily for discounters, rather than non-discounters. This is particularly interesting as it suggests that the subjective choice measures of intertemporal discounting analysed here could potentially be useful tools to screen for those at high risk of weight gain after smoking cessation.

5.2 Intertemporal Discounting and Smoking

5.2.1 Background

Smoking

'Smoking' usually refers to the act of smoking tobacco, usually through cigarettes, cigars or pipes. While the term can be used in reference to smoking other substances, the term 'smoking' will be used in this thesis to refer solely to tobacco smoking unless otherwise noted. When individuals are defined as 'current smokers' this refers to someone who smokes regularly, where the amount of smoking required for the definition may vary slightly based on the data source.

Knowledge of the adverse health effects of smoking has increased over the latter half of the twentieth century. Smoking prevalence in Australia has been decreasing over recent years, due to the combined effects of this increasing health knowledge regarding smoking, changing social attitudes towards smoking, and various government initiatives to reduce smoking such as informational campaigns, increased taxation, and restrictions on legal smoking locations. The downward trend in the prevalence of current smokers among Australians over the last few decades is depicted in Figure 5.1 and Figure 5.2, for the adult and youth populations respectively.

Figure 5.1: Prevalence of Current Smokers aged 18+, Australia

NOTE:
This figure is included on page 150 of the print copy of the thesis held in the University of Adelaide Library.

Source: National Preventative Health Taskforce (2009)

Figure 5.2: Trends in Current (Weekly) Smoking for Youths, Australia

NOTE:
This figure is included on page 150 of the print copy of the thesis held in the University of Adelaide Library.

Source: National Preventative Health Taskforce (2009)

Figure 5.3: Change in smoking rates by gender, 1990 to 2005

NOTE:
This figure is included on page 151 of the print copy of the thesis held in the University of Adelaide Library.

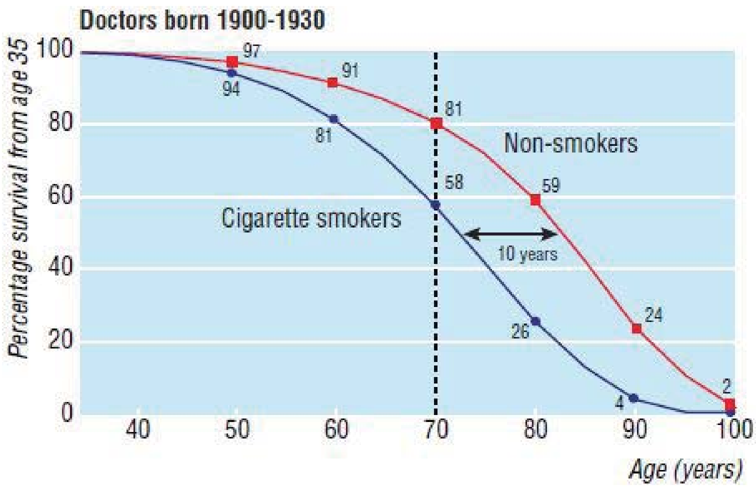
Source: OECD (2007)

This trend is not atypical of international experiences, in particular many OECD countries have experienced significant reductions in smoking prevalence over the last several decades, as shown in Figure 5.3. However, there are also countries where the prevalence is still very high, in particular China has a smoking prevalence among males of around 67% (World Health Organization 2002).

Although smoking prevalence has fallen in Australia, the costs of tobacco smoking are still high. A recent report suggested that the social costs of smoking were as high as $31 billion (Collins and Lapsley 2009), although this figure has been contested.

Before discussing the intertemporal choice aspect of smoking, it is important to understand better the time profile of the personal health costs of smoking. A major health cost of smoking is the increased mortality risk of smokers versus non-smokers. Figure 5.4 shows the percentage survival of smokers and non-smokers in a sample of male British doctors. The survival rates diverge more noticeably after a decade or two, so it is clear that if a potential smoker is aware of these relationships, they will consider a large part of the mortality risk of smoking to come in the future. While the figure shown is but one example commencing at a particular age, and looking at a particular sample, similarly shaped curves are generally found for comparisons in other samples and from other commencement ages. It will be taken as given throughout this chapter that a large part of the health costs of smoking come in 'the future'. While not presented in detail here, the evidence in the literature on the mortality and morbidity costs of smoking bear this assertion out.

Figure 5.4: Survival Rate from Age 35, of a Sample of Smoker and Non-Smoker UK Doctors



Source: Doll et al. (2004)

Theoretical Background

While the general models of health capital accumulation such as Grossman (1972) could be applied to smoking behaviour, these general models do not usually account for the addictive nature of the good explicitly, and so miss an important part of the story. As such, theoretical models of smoking behaviour are generally based on models of addiction. In reviewing the literature, Chaloupka and Warner (2000) divide these smoking models into three categories: imperfectly rational addiction models, myopic addiction models, and rational addiction models. The most popular type of model of smoking behaviour in recent years, in the economic literature at least, are the rational addiction models, and in particular Becker and Murphy's (1988) model of rational addiction. The type of model one chooses to subscribe to, and indeed the specific model, will of course have implications for how one would expect intertemporal discounting to be related to smoking behaviour.

The elegantly simple rational addiction model of Becker and Murphy models a finitely-lived consumer who maxmises their perceived lifetime utility from the present period:

$$U(0) = \int_0^T e^{-\sigma t} u[y(t), c(t), S(t)]dt \tag{5.1}$$

The individual's period utility $u[\cdot]$ depends on addictive consumption $c(t)$, non-addictive consumption $y(t)$, and stock of addictive 'consumption capital' $S(t)$. This stock is added to by consumption of the addictive good, depreciates over time, and can be modified by 'investment'. The present value of lifetime utility depends on the stream of period utilities discounted exponentially at the discount rate σ. Period utility $u(t)$ is assumed to be jointly separable in $c(t)$, $y(t)$ and $S(t)$, so that all effects of addictive consumption on future periods occur through the stock variable.

The model contains further assumptions on the utility function, asset accumulation, the path of the stock variable and so on, which need not be presented here for this brief introduction. There are two important assumptions for the addictive nature of the good. That the partial derivative of the period utility function with respect to the stock variable is negative, which means that higher previous consumption of the addictive good will lower the utility received from a given consumption vector; in the case of smoking this means that a higher level of past smoking reduces current utility from a given consumption vector. The second important assumption is that an increased addictive stock will raise the marginal utility of addictive consumption; in the case of smoking this means that the higher the level of past smoking, the higher the marginal utility of smoking will become. This model can explain various aspects of addiction, including binges and 'going cold-turkey', in a framework of a rational, forward-looking consumer, and this is why it and its variants have become so popular.

Becker and Murphy (1988) recognised that individuals' heterogeneous rates of intertemporal discounting were important in this model as an explanation of the differing optimal consumption paths of consumers.

> *... an increase in the rate of preference for the present and in the depreciation rate on consumption capital raises the demand for harmful goods but lowers the demand for beneficial goods. As a result, drug addicts and alcoholics tend to be present-oriented, while religious individuals and joggers tend to be future-oriented.*

Intuitively, there should be a strong relationship between intertemporal discounting and smoking behaviours for two reasons. Firstly, an individual with a higher discount rate would take less heed of the future health costs of smoking, and thus they would smoke more, or be more likely to commence smoking. Secondly, as a forward-looking agent we would expect the individual to realise that any smoking now will have an adverse effect on themselves through addiction, and this future addiction cost would also be discounted more by an individual with a higher discount rate. Importantly, both these effects are captured in the model of rational addiction just described.

One of the important reasons for the predominance of the rational addiction model, is that its implications have commonly been supported by empirical analyses. For example the model's predictions with regard to changes in prices on smoking are supported in many papers[1]. However, while the importance of intertemporal discounting has been recognised by authors such as Bretteville-Jensen (1999), the implications from the model of rational addiction of the important relationship between intertemporal discounting and smoking have not been as widely analysed empirically. When these questions have been empirically analysed, the results have not always been as expected, and this will be discussed further in the following subsection.

Although it is the most commonly cited, the Becker and Murphy (1988) model of rational addiction is not alone in terms of rational addiction models[2]. Furthermore, there is a growing literature of models specifically of smoking behaviour that contain their own nuances and contributions[3]. This literature has not been addressed further here as it does not add much to the story of this chapter. Indeed many of these models are based on similar ideas of rational addiction, and similarly would suggest that a high intertemporal discount rate is an important determinant of smoking behaviour.

[1]See for example Chaloupka (1991), Becker, Grossman, and Murphy (1994), Labeaga (1999), Gruber and Köszegi (2001), and Adda and Cornaglia (2006)

[2]See for example Stigler and Becker (1977), Dockner and Feichtinger (1993), Orphanides and Zervos (1995), and Gruber and Köszegi (2001)

[3]See for example Chaloupka (1991), Suranovic, Goldfarb, and Leonard (1999), Jones (1999), and Carbone, Kverndokk, and Rogeberg (2005)

One final issue of theoretical concern, is the suggestion by Becker and Mulligan (1997) that causality between intertemporal discounting and smoking for example could go in the opposite direction, that is from smoking to discount rate. This possibility should not be discounted, but generally the assumption will be made that this is not the case, or that the effect is negligible relative to the expected main effect.

Previous Empirical Findings

The body of empirical evidence regarding the relationship between intertemporal discounting and smoking behaviour could be considered either small, or relatively large, depending on how broadly the area is defined. This is because as well as works from economics that relate discount rates to hypotheses from a model of rational addiction, there is also a large body of literature in areas such as psychology, that look at the relationship of psychological concepts such as 'impatience' and 'impulsivity' with smoking behaviour. Indeed the psychology literature even refers often to concepts of intertemporal discount rates, using the term 'delay discounting', which is perhaps less commonly used terminology in the field of economics. The following paragraphs briefly review these literatures, discussing the empirical results found in analyses of smoking and indicators of intertemporal discounting, that may be revealed preference indicators and naturally occurring proxies, elicited personality trait indicators, or stated preference indicators.

In an early analysis to empirically test the predictions of Becker and Murphy's (1988) theory of rational addiction with respect to smoking, Chaloupka

(1991) included a subsection on 'time preference and addiction', recognising the importance of this to the model. They use the assumptions that time preferences will differ systematically with age and eduction, in particular that less educated and younger individuals will behave more myopically. They use results such as the fact that less educated individuals are more responsive to prices to infer support for hypotheses derived from the model. While these results are interesting, since there are a large number of other factors that may change with age and education, there is a limit to how confidently these results can be related to intertemporal discounting. More recently, Scharff and Viscusi (2010) have found that rates of time preference elicited from wage-fatality risk tradeoffs are higher for smokers than non-smokers. The importance of the results depends strongly on your beliefs in the revealed preference approach to estimating intertemporal discount rates.

In the psychology literature, smoking behaviour has been shown to be correlated with a number of personality traits such as impulsivity, short temporal horizon, and low self-discipline (Mitchell 1999, Terracciano and Costa 2004, Ohmura, Takahashi, and Kitamura 2005, Jones et al. 2009, Doran et al. 2009). While these results are interesting and in a similar area to the original work presented in this chapter, the constructs that are being measured in this literature are sufficiently different that it is difficult to compare this chapter's results to them. In addition this literature often does not control for demographics and other variables, which makes it difficult to ascertain whether the correlations are being driven by other factors such as education and income. Khwaja, Silverman, and Sloan (2007) within the same study looked at the associations between smoking and both stated preference discount rates and subjective measures of 'impulsivity' and 'planning'. Interestingly the latter measures were more strongly associated with smoking behaviour, so clearly the importance of these personality traits as constructs should not be underestimated, but they are clearly different to the concepts of intertemporal discounting that are addressed in this chapter, the analysis of which is interesting in its own right.

In his seminal paper Fuchs (1982) was the first to publish an empirical analysis of the relationship between stated preference indicators of intertemporal discounting and health behaviours and outcomes. A variable to represent intertemporal discounting was constructed using responses to a series of questions in which respondents were asked to choose between the hypothetical receipt of a sum of money now, and a larger amount at a future date, with the amounts varied in order to estimate the respondent's discount rate. Strategies similar to this have been widely used in similar work since then. Fuchs (1982) found a significant positive effect of the implied discount rate on the number of cigarettes smoked per day, however he notes that the marginal effect is small, and the explained variation in cigarettes smoked by the regression is also small.

A number of studies in the past decade have related intertemporal discounting indicators elicited from stated preference choices to smoking behaviour. The majority of these studies have found evidence of relationships between a higher rate of intertemporal discounting and smoking probability or quantity (Bickel, Odum, and Madden 1999, Odum, Madden, and Bickel

2002, Baker, Johnson, and Bickel 2003, Ohmura, Takahashi, and Kitamura 2005, Ida and goto 2009, Audrain-McGoverna et al. 2009). However Khwaja, Silverman, and Sloan (2007) find no significant relationship, and Chesson and Viscusi (2000) find that smokers have a significantly lower mean discount rate. Unfortunately, although these studies excel in many ways by containing many aspects in their analyses that cannot be covered here, they are lacking in two main respects. Firstly, a large number of them have quite small sample sizes with below 200 observations, and some not even exceeding 50 observations. Secondly, many of the studies obtain their results by looking at how smoking outcomes differ with changes in discounting (or vice versa), without conditioning on other potential explanatory variables. None of these studies explicitly condition on income or education for example, so it becomes difficult to necessarily infer a separate conditional association between a higher discount rate and a higher probability of smoking. It could be that a higher discount rate is associated with certain education and income outcomes, which in turn are associated with smoking outcomes. While an unconditional marginal effect of discount rate on smoking outcomes has its own useful interpretations, it may be more interesting to find the association between discounting and smoking behaviour after conditioning on other variables such as these. Thus the empirical work presented in this chapter will provide an innovative contribution to the literature by estimating the partial effect of intertemporal discounting on smoking outcomes, conditional on a set of demographic variables.

The issue of whether a higher rate of intertemporal discounting causes smoking as proposed in the previous subsection, or whether the causation happens in the other direction as suggested by Becker and Mulligan (1997) has also been addressed in the literature. Audrain-McGoverna et al. (2009) use a longitudinal cohort of adolescents to investigate this, and find that the degree of delay discounting did not change significantly over time, and that there is little evidence of smoking impacting delay discounting. They do of course also find that a higher degree of delay discounting does have a significant effect on the odds of taking up smoking. This result is supported by Bickel, Odum, and Madden (1999) who find that former smokers and never smokers have similar discount rates, while current smokers have higher ones. They suggest that while this could mean that smoking causes higher discount rates, the evidence in their frequency distributions of discount rates suggest that it is instead a self-selection effect, whereby those smokers with lower discount rates are more likely to quit. Ida and Goto (2009) find that former smokers have a lower discount rate even than never smokers, and it is likely that this is also due to the self-selection effect. Of course it may be that the causality does indeed go in both directions, however the evidence seems to suggest that at least the majority of the relationship between discounting and smoking is in the direction of discounting affecting smoking. In the discussion in this chapter it will generally be assumed that this is the case.

5.2.2 Data

The dataset used for this analysis is the South Australian Health Omnibus Survey conducted in Spring 2008. This population representative dataset has also been used in Chapter 3 and Chapter 4. The key variables related to intertemporal discounting are discussed in detail in Chapter 3. The other variable definitions and summary statistics are available in Chapter 4. This is the first chapter to use variables related to smoking behaviours, so these will be introduced briefly here.

A 'current smoker' refers to a respondent who stated they smoke daily, a 'former smoker' is a respondent who once smoked daily but no longer does, and a 'never smoker' is a respondent who reported never having smoked on a daily basis.

The (unweighted) prevalence of current daily smoking in the sample (n=1868) is 16.86%, and the proportion of former smokers is 30.19%. These figures are relatively similar to other datasets, for example estimates from the 2004 National Drug Strategy Household Survey indicate that around 17.4% of Australians age 14 and over were current smokers, and a further 26.4% were former smokers (defined as having smoked 100 cigarettes or a similar amount of tobacco over their lifetime and no longer smoking). As in the previous chapters weights will not be used in the analysis for the reasons already described.

5.2.3 Analysis

Table 5.1 shows the proportion of individuals in the sample in each of the three smoking categories (current, former, and never), looking separately at various subsamples defined by demographic variables. This shows a number of interesting aspects of smoking behaviour in the sample. For example,

Table 5.1: Proportion of Respondents in Each Smoking Status by Demographics (%)

Demographic	Current Smoker	Former Smoker	Never Smoker	n
Full Sample	16.86	30.19	52.94	1868
Discounting Indicators				
Monetary Domain Discounter	23.03	30.34	46.63	356
Not Monetary Domain Discounter	15.41	30.16	54.43	1512
Health Domain Discounter	13.99	31.62	54.40	193
Not Health Domain Discounter	17.19	30.03	52.78	1675
Sex				
Male	18.98	34.52	46.50	843
Female	15.12	26.63	58.24	1025
Age Range				
15-24	16.03	9.16	74.81	131
25-44	23.19	22.71	54.10	634
45-64	18.03	34.79	47.18	710
≥65	4.83	40.97	54.20	393
Annual Income				
<$20000	23.51	37.30	39.18	319
$20000-49999	17.77	33.52	48.72	546
$50000-100000	16.43	24.33	59.24	633
>$10000	10.54	29.19	60.27	370
Highest Qualification				
Bachelor degree or higher	8.42	22.89	68.68	380
Certificate/Diploma (>1FTE)	12.50	31.25	56.25	272
Certificate/Diploma (≤1FTE)	18.06	31.28	50.66	227
Trade/Apprenticeship	20.49	35.66	43.85	244
Left school after 15, still studying	26.87	25.37	47.76	67
Left school after 15	19.58	34.03	46.39	429
Left school at 15 or less	24.89	31.67	43.44	221
Still at school	3.57	3.57	92.86	28
Functional Health Literacy				
Adequate	15.64	27.31	57.05	1106
At Risk	19.58	30.77	49.65	429
Inadequate	17.42	39.04	43.54	333
BMI Group				
Underweight	22.22	22.22	55.56	36
Normal weight	17.37	24.58	58.05	708
Overweight	15.78	30.80	53.41	659
Obese	17.20	38.49	44.30	465

while the prevalence of current smoking in the total sample is 16.86%, the prevalence among those with a bachelor degree or higher is less than half that at only 8.42%. Smoking prevalence is higher in lower income groups, is higher for males than females, and for those in an intermediate age range. This table is illustrative of the varying prelavence of smoking amongst various subsamples, these relationships will be more formally analysed shortly.

Looking at the indicator of a positive intertemporal discount rate in the monetary domain shows a notably higher prevalence of current smoking amongst discounters, compared to non-discounters. A χ^2 test of the hypothesis that there is a relationship between smoking status and the monetary discounting indicator finds that there is a statistically significant relationship between the variables (p-value: 0.001).

On the other hand, the health-domain indicator of intertemporal discounting seems to be correlated with smoking status in the 'wrong' direction. In fact a χ^2 test finds that there is no statistically significant relationship between smoking status and the health-domain indicator (p-value: 0.527). This is similar to the insignificance of the health-domain indicator found in Chapter 4. As suggested previously, it may be that this indicator is not a good reflection of the characteristic it was intended to capture. For this reason, the health-domain variable will be excluded from much of the ensuing analysis presented here. Its inclusion does not change the qualitative nature of most of the results, nor does it greatly change the quantitative estimates.

Estimation of Binary Outcome Models of Smoking

An aim of this chapter is to estimate the effect of intertemporal discounting on smoking outcomes, after controlling for other factors using multivariate techniques. However this question should be addressed differently depending on how 'smoking outcomes' is interpreted, as individuals can be grouped into three categories: current smokers, former smokers, and never smokers. It would make sense to estimate a multinomial model that allows for these three outcomes separately, and this will be done in the next subsection. However in this subsection the analysis will be restricted to binary models, since many other papers on a similar topic take this approach, and it will be useful to contrast the results here to their results, and to the results using multinomial outcome specifications.

One possible approach is to compare current smokers to non-smokers, where 'non-smoker' includes both former smokers and never smokers (Chesson and Viscusi 2000). Another approach is to exclude former smokers from the sample, so that the comparison is simply between current smokers and never smokers (Baker, Johnson, and Bickel 2003, Ohmura, Takahashi, and Kitamura 2005). As well as these two, to attain a picture as complete as is possible with binary methods, models will also be estimated for the other possible binary comparisons: former smokers versus never smokers; current smokers versus former smokers; and never smokers versus the combined set of current and former smokers.

Denote the outcome variable y, taking the value of 1 for the positive outcome of the estimated model (e.g. current smoker), and the value 0 otherwise. Here the aim is to estimate a model that estimates the probability of outcome y_i for an individual, conditional on a $K \times 1$ vector of explanatory variables $\mathbf{x}_i$, which includes the discounting indicator, as well as controls for age, sex, income, education, and functional health literacy.

$$Pr(y_i = 1|\mathbf{x}) = F(\mathbf{x}'\beta) \tag{5.2}$$

The function F should be a cumulative distribution function with the domain $(-\infty, \infty)$ so that the probability is bounded between zero and one.

This model can be interpreted as a latent variable model.

$$y^* = \mathbf{x}'\beta + u \tag{5.3}$$

$$y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases} \tag{5.4}$$

Where the latent variable y^* depends linearly on the explanatory variables $\mathbf{x}$ and an error term u.

If the error term u is standard normally distributed, then this is the probit model, and if it is logistically distributed it is the logit model. The results presented in Table 5.2 are for the logit model, the probit model estimations produce qualitatively similar results so have not been reported here.

In the context of this model, the estimate of interest is β, and in particular the element of β corresponding to the discounting indicator variable contained in $\mathbf{x}$. Table 5.2 presents odds ratios derived from the estimated β coefficients rather than the estimated coefficients themselves, for ease of quantitative interpretability. The relationship is simply OR= e^{β}_{j}, where β_j is the corresponding element of the estimated β. Robust standard errors shown are similarly transformed. Odds ratios greater than 1 indicate that the RHS variable has a positive relationship with the odds of an individual being in the dependent variable category of interest.

Table 5.2 shows the estimation results of the various binary comparisons possible using the three previously defined subgroups of current smokers, former smokers and never smokers as the dependent variable y. The same vector x of explanatory variables is used for each model specification; including the monetary discounting indicator, and controlling for age, sex, income, education, and functional health literacy. A squared term is included for age to account for the non-linear relationship between age and smoking status. The associations between smoking behaviour and the demographic controls are generally as expected, with for example lower education and income associated with smoking behaviour. These estimated relationships will not be commented on further, as they are not the primary objects of concern.

Looking at the result of interest, the estimate of the effect of being a monetary discounter on smoking outcomes is positive in each of the specifications, but significant in only the second, third and fifth specifications. These results point to discounting as an important determinant of becoming a smoker rather than a never smoker. However there is no statistically significant impact of intertemporal discounting on being a former smoker rather than a current smoker, after controlling for the other covariates. This suggests that intertemporal discounting, as measured by the stated choice indicator, is more appropriately considered as a trait that influences the commencement

Table 5.2: Estimation of Smoking Outcomes: Binary Logit (Odds Ratios)

$y=1$ $y=0$	current former and never	current never	current and former never	current former	former never
PDR-M	1.216	1.431**	1.307**	1.003	1.300*
	(0.1925)	(0.2468)	(0.1635)	(0.1903)	(0.1896)
Age	1.154***	1.206***	1.092***	1.039	1.092***
	(0.0375)	(0.4317)	(0.194)	(0.0369)	(0.1896)
Age squared	0.998***	0.998***	0.999***	0.999***	0.999***
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0002)
Female	0.732**	0.581***	0.581***	0.916	0.584***
	(0.1011)	(0.0872)	(0.0593)	(0.1512)	(0.0680)
Highest Qualification					
Bachelor degree or higher			(Base Group)		
Certificate/Diploma (>1FTE)	1.788**	1.954**	1.641***	1.206	1.457*
	(0.4824)	(0.5503)	(0.2846)	(0.3712)	(0.2805)
Certificate/Diploma (≤1FTE)	1.984**	2.592***	1.994***	1.150	1.833***
	(0.5398)	(0.7541)	(0.3682)	(0.3691)	(0.3869)
Trade/Apprenticeship	2.629***	3.045***	2.103***	1.673*	1.737***
	(0.6804)	(0.8444)	(0.3856)	(0.5107)	(0.3558)
Left school after 15, still studying	3.565***	4.226***	2.453***	2.340*	2.019**
	(1.2544)	(1.5933)	(0.6627)	(1.0435)	(0.6660)
Left school after 15	2.329***	3.275***	2.258***	1.126	2.032***
	(0.5556)	(0.8370)	(0.3667)	(0.3164)	(0.3796)
Left school at 15 or less	5.013***	5.979***	2.241***	2.613***	1.435
	(1.4291)	(1.8940)	(0.4520)	(0.8538)	(0.3319)
Still at school	0.351	0.316	0.206**	3.669	0.2126
	(0.4012)	(0.3784)	(0.1604)	(5.001)	(0.2180)
Household Income Range					
≥ \$100000			(Base Group)		
\$80001-\$100000	1.298	1.140	0.966	1.511	0.888
	(0.3437)	(0.3170)	(0.1768)	(0.4690)	(0.1850)
\$60001-\$80000	1.369	1.165	0.944	1.649*	0.804
	(0.3386)	(0.3063)	(0.1656)	(0.4748)	(0.1612)
\$50001-\$60000	1.768**	1.375	0.801	2.821***	0.547**
	(0.4877)	(0.4058)	(0.1644)	(0.9708)	(0.1379)
\$40001-\$50000	1.968**	1.757*	1.320	2.029**	1.060
	(0.5325)	(0.5160)	(0.2688)	(0.6391)	(0.2469)
\$30001-\$40000	2.024**	1.743*	1.211	2.357***	0.905
	(0.5653)	(0.5273)	(0.2548)	(0.7442)	(0.2175)
\$20001-\$30000	1.949**	1.908**	1.287	1.812*	0.979
	(0.5627)	(0.5888)	(0.2529)	(0.5784)	(0.2182)
\$12001-\$20000	3.791***	4.895***	2.103***	3.055***	1.402
	(1.0446)	(1.4875)	(0.4341)	(0.9908)	(0.3283)
≤ \$12000	3.947***	4.401***	2.103***	4.205***	1.343
	(1.3808)	(1.9537)	(0.5790)	(1.7576)	(0.4154)
Functional Health Literacy					
Adequate			(Base Group)		
At Risk	1.326*	1.450**	1.145	1.282	1.012
	(0.2220)	(0.2595)	(0.2051)	(0.2533)	(0.1481)
Inadequate	1.337	1.405	1.339*	1.254	1.270
	(0.2677)	(0.3194)	(0.1455)	(0.2944)	(0.2161)
Observations	1868	1304	1868	879	1553
Pseudo R^2	0.1274	0.1587	0.0668	0.1426	0.0669
Log pseudolikelihood	-739.5548	-606.533305	-1205.2476	-491.76286	-949.4931

The estimates shown for each variable have been transformed from the coefficient estimates to odds ratios for ease of interpretability. Robust standard errors for the odds ratios are shown in parentheses. Statistical significance of coefficients are indicated in the usual way (* for p<0.10; ** for p<0.05; *** for p<0.01) of smoking rather than quitting. This result is in agreement with Audrain-Mcgoverna et al. (2009), who use quite a different methodology to come to similar conclusions.

Controlling for the other covariates using a multivariate model is important for these results, and although not a particularly technical advancement, is something that often has not been done in the preceding literature. To see how not controlling for the covariates specified would bias the results, Table 5.3 shows the results that would have been obtained using only the monetary discounting indicator as an explanatory variable. Clearly these results give quite a different impression, that former smokers are more akin to never smokers than current smokers in terms of discounting behaviour. And this is indeed true for unconditional associations, however, after conditioning on a vector of demographic covariates, as in Table 5.2, quite the opposite seems to be true.

Table 5.3: Estimation of Smoking Outcomes: Binary Logit Models Without Controlling for Covariates (Odds Ratios)

$y = 1$ $y = 0$	current former and never	current never	current and former never	current former	former never
PDR-M	1.643*** (0.2377)	1.745*** (0.2689)	1.367*** (0.1615)	1.486** (0.2485)	1.174 (0.1606)

The estimates shown for each variable have been transformed from the coefficient estimates to odds ratios for ease of interpretability. Robust standard errors for the odds ratios are shown in parentheses. Statistical significance of coefficients are indicated in the usual way (* for p<0.10; ** for p<0.05; *** for p<0.01)

Clearly the conclusion drawn in the preceding paragraphs that discounting is an important determinant of the transition to smoking, but less important for the transition from smoking is drawn tenuously, since the logit models employed do not take into account the sequential nature of these transitions, or even the relationship between the multiple outcomes. It may be an improvement to estimate the effect of intertemporal discounting on smoking outcomes through a sequential model.

Sequential Logit Specification

Individuals make two decisions. Firstly they decide whether or not to commence regular smoking, or remain a never smoker. Then, as a smoker they decide whether to continue as a current smoker, or to quit and become a former smoker. Of course it is not certain that the status reported by the individual will not change in the future, so this model should be thought of as describing possible transitions to the individuals *current observed* smoking status. This transition path is depicted in Figure 5.5.

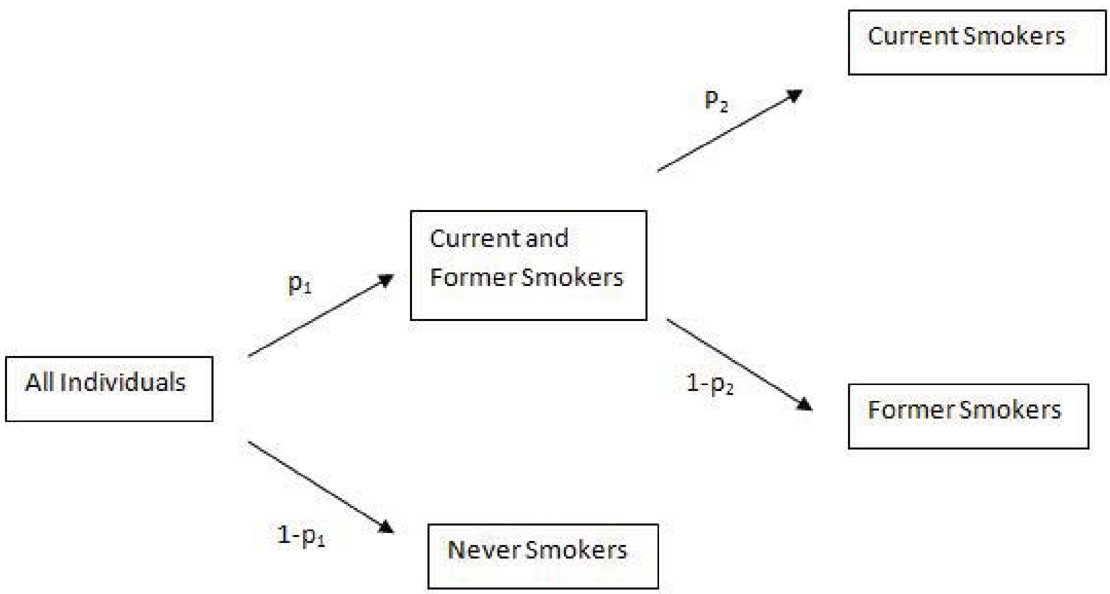
With probability p_1 the individual commenced regular smoking at some point, and conditional on that occurrence, the probability that the individual has not to this date quit smoking is given by p_2. The conditional and unconditional probabilities of currently being in each state are summarized in Table 5.4

Table 5.4: Smoking Status Probabilities

Prob(never)	$(1 - p_1)$
Prob(current)	$p_1(1 - p_2)$
Prob(former)	$p_1 p_2$
Prob(current$\|${current,former})	p_2
Prob(former$\|${current,former})	$1 - p_2$

The probabilities p_1 and p_2 will depend on a variety of explanatory variables. The same vector $\mathbf{x}$ of explanatory variables as in the previous

Figure 5.5: Transition Path of Smoking Behaviour



section is assumed as explanatory variables, including of course the indicator of intertemporal discounting. The logistic distribution is assumed ($\Lambda(z) = \frac{exp(z)}{1+exp(z)}$) as in the previous section.

$$p_1 = \Lambda(\beta_1 \mathbf{x}) \tag{5.5}$$

$$p_2 = \Lambda(\beta_2 \mathbf{x}) \tag{5.6}$$

This sequential logit model is estimated using maximum likelihood, and the results are presented below in Table 5.5. The estimated β coefficients are presented and these can be interpreted as log odds ratios.[4]

It appears again that intertemporal discounting, as represented by the stated-choice indicator, is a significant determinant of the probability that an individual has commenced regular smoking. However, it is not significantly associated with the probability of having quit smoking, conditional on commencement at some prior time.

For the probability of having commenced regular smoking at some point, the significant variables have their expected signs. Lower levels of educational attainment are positively associated with smoking commencement, as are having lower incomes, and having inadequate functional health literacy. Females are less likely to have commenced smoking than males, and age shows a quadratic relationship with the log odds of smoking commencement, with a positive impact at younger age ranges, turning around to a negative effect at around the age of 50. For smoking continuation (not having perma-

[4]More specifically the estimation was undertaken using the user-written *seqlogit* routine (Buis 2007) for the STATA statistical package (StataCorp 2007).

Table 5.5: Estimation of Smoking Outcomes: Sequential Logit Model

	Estimation of p_1	Estimation of p_2
PDR-M	0.2675**	0.0033
	(0.1254)	(0.1896)
Age	0.0878***	0.0379
	(0.0178)	(0.0355)
Age squared	-0.0009***	-0.0010***
	(0.0002)	(0.0004)
Female	-0.5419***	-0.0879
	(0.1020)	(0.1651)
Highest Qualification		
Bachelor degree or higher	(Base Group)	
Certificate/Diploma (>1FTE)	0.4950***	0.1875
	(0.1735)	(0.3077)
Certificate/Diploma ($\leq$1FTE)	0.6903***	0.1400
	(0.1847)	(0.3208)
Trade/Apprenticeship	0.7435***	0.5147*
	(0.1833)	(0.3052)
Left school after 15, still studying	0.8974***	0.8500*
	(0.2701)	(0.4459)
Left school after 15	0.8146***	0.1184
	(0.1623)	(0.2810)
Left school at 15 or less	0.8071***	0.9603***
	(0.2016)	(0.3267)
Still at school	-1.580**	1.300
	(0.7785)	(1.3626)
Household Income Range		
$\geq$ \$100000	(Base Group)	
\$80001-\$100000	-0.0341	0.4127
	(0.1829)	(0.3103)
\$60001-\$80000	-0.0579	0.5000*
	(0.1755)	(0.2879)
\$50001-\$60000	-0.2214	1.0370***
	(0.2051)	(0.3441)
\$40001-\$50000	0.2775	0.7073**
	(0.2037)	(0.3150)
\$30001-\$40000	0.1917	0.8572***
	(0.2103)	(0.3157)
\$20001-\$30000	0.2523	0.5945*
	(0.1965)	(0.3191)
\$12001-\$20000	0.7433***	1.117***
	(0.2064)	(0.3242)
$\leq$ \$12000	0.7435***	1.436***
	(0.2753)	(0.4179)
Functional Health Literacy		
Adequate	(Base Group)	
At Risk	0.1354	0.2483
	(0.1271)	(0.1976)
Inadequate	0.2920*	0.2264
	(0.1532)	(0.1976)
Observations	1868	
Log pseudolikelihood	-1697.0105	

The coefficient estimates shown can be interpreted as log odds ratios. Robust standard errors are shown in parentheses. Statistical significance of coefficients is indicated in the usual way (* for p<0.10; ** for p<0.05; *** for p<0.01) nently quit at some point), only age, education and income have statistically significant coefficients.

Both the sequential model analysis and the binary model analyses suggest that higher intertemporal discounting rates are associated with both being a current smoker and being a former smoker. This suggests that having a high discount rate is a stable trait that is a determinant of smoking behaviour, rather than a result of smoking as suggested by some researchers. If it was smoking that caused the high discount rate rather than the other way around, one would expect to see the discount rate of former smokers to more closely resemble that of never smokers, once other relevant covariates were controlled for; and this was not the case here. Evidence has also been shown that the degree of intertemporal discounting is a more important determinant of smoking commencement rather than smoking cessation. Thus if one was to propose using measures of intertemporal discounting as a diagnostic tool, it would be useful to identify groups of individuals at risk of smoking commencement.

5.3 Obesity, Smoking and Intertemporal Discounting

5.3.1 Background

In Chapter 4 of this thesis evidence was presented of a relationship between intertemporal discounting, as represented by a stated-preference choice in the monetary domain, and body mass outcomes. Further, it was suggested that this relationship may be more pronounced for those individuals that were categorized as 'obese'. In the earlier part of this chapter, evidence was shown of a relationship between discounting and smoking behaviour. It was there shown that after controlling for other demographics, there is a positive relationship between discounting and being categorised as both current and former smokers. Since both body weight outcomes and smoking outcomes are partially determined by similar factors such as discounting, age, sex, income and education, an association between smoking and body weight should be expected based simply on individuals' characteristics. Furthermore, there is evidence of a negative direct causal relationship between smoking and body weight (Filozof, Pinilla, and Fernndez-Cruz 2004).

These relationships have some implications for the previous analysis in Chapter 4 of this thesis regarding the relationship between intertemporal discounting and body weight outcomes. Assume that smoking has a direct negative impact on BMI, and that a higher rate of intertemporal discounting will *ceteris paribus* result in a higher BMI, and *ceteris paribus* result in a higher probability of smoking. Then there is a direct effect of discounting on BMI, a direct effect of discounting on smoking, and also an indirect effect of discounting on BMI through smoking. This could suggest that estimates of the relationship between intertemporal discounting and body weight that do not take the mitigating effect of smoking into account could underestimate this effect. This possibility will be examined in the forthcoming analysis.

There is also considerable debate in the literature about the link between smoking and obesity. Using the same data set, but different methodology, Chou, Grossman, and Saffer (2004) and Gruber and Frakes (2006), find opposite results; the former finding a positive relationship between cigarette price and body weight, and the latter finding a negative effect of cigarette taxes on body weight. This debate has been continued more recently by (Baum 2009), who finds results supporting a negative relationship between smoking and BMI or obesity. Au, Hauck, and Hollingsworth (2009) controlling for the standard variables, find that factors that are unobserved in their empirical specifications play a significant role in the relationships between obesity and smoking for women; intertemporal discounting could be one such factor. Robb, Huston, and Finke (2008) suggest that estimates of the negative relationship between smoking and BMI that do not control for time preference will be underestimated, since a high rate of time preference will positively impact both. They report results that are contended to support this hypothesis. This chapter will also attempt to examine this issue using different methodologies and assumptions.

5.3.2 The Relationship Between Discounting and Obesity: Smoking as a Mitigating Factor

As described above, the indirect causal pathway from intertemporal discounting to body weight outcomes through smoking behaviour can operate as a mitigating factor against the more direct effects from discounting to body weight. Intertemporal discount rate may effect the probability of smoking for all individuals, but the negative effect of smoking on body weight only occurs for those individuals that *actually* are smokers, rather than those who have a high estimated probability of smoking. So for individuals that are not smokers, then the effect of intertemporal discount rate on body weight outcomes will not be biased by the indirect effect through smoking.

A higher discount rate not only would theoretically be associated with an increased likelihood of smoking so long as the consumer is not myopic, but also potentially an increased quantity of smoking. Assuming increased smoking has a negative effect on BMI, then the mitigating effects may also occur *within* the population of smokers through smoking quantity.

Thus the expectation is that the effect of intertemporal discounting on the body weight outcomes of non-smokers will be higher than the effect for current smokers. In addition it would be expected that the estimated effect of intertemporal discounting on body weight outcomes will be reduced through the effects of discounting on the probability of smoking, if not controlled for.

This section re-estimates a number of model specifications of body weight determination from Chapter 3, including linear regression on BMI, and also models of the probability of obesity. There is a particular focus on the association between discounting behaviour and the BMI category 'obese', due to obesity's clinical importance, as well as the findings in the previous chapter that intertemporal discounting may be more important in this region of the BMI distribution. The variable representing discounting in the health domain (PDR-H) is not included in the models, due to the potential problems with it discussed in previous chapters. These models are re-estimated in three ways to look at the suggested hypotheses. An indicator variable for current smoking is introduced into the models, to see how controlling for current smoking modifies the outcome. Here it is implicitly assumed that the mitigating effect of smoking on the estimation occurs only through the probability of smoking. Further specifications are presented that include an interaction term for smoking and positive intertemporal discounting. These regressions consider the potential that the effect of intertemporal discounting on body weight outcomes may differ by smoking status. Finally separate regressions are estimated for the sub-samples of current smokers and non-smokers, allowing the marginal effects of all explanatory variables to vary across the subsamples. These regression results are presented in Table 5.6 and Table 5.7.

Consider first columns (1) to (3) of Table 5.6. These multivariate linear regression estimates on BMI differ only in the inclusion of an indicator of smoking, and an interaction of this variable with discounting[5]. Column (1) is comparable to the models estimated in Chapter 4, where smoking was not incorporated in the analysis, the result of interest is the estimated coefficient on PDR-M, which shows that an individual that is a discounter in the monetary domain has on average a BMI 1.1 units higher than an individual who is not a discounter, controlling for the other variables in the model. In specification (2) a binary variable indicating whether an individual is a current smoker or not is included. Smoking has a statistically significant negative

[5]The AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) can be used for model selection. For both measures, the lower the value the better the model explains the data. Comparing models (1) to (3), the AIC prefers (3), then (2), then (1), while the BIC ranks the models in the exact opposite direction, so unfortunately there is little evidence of which model is a better fit for the data. Since models (4) and (5) use different subsamples it is not appropriate to compare them in this way.

Table 5.6: Linear Regressions on BMI, With and Without Smoking Variables

	(1) No Variables	(2) Smoking Indicator	(3) Interaction Term	(4) Smokers Only	(5) Non-Smokers Only
PDR-M	1.100***	1.126***	1.417***	0.201	1.386***
	(0.346)	(0.346)	(0.399)	(0.690)	(0.399)
Current Smoker		-0.817**	-0.483		
		(0.350)	(0.401)		
(PDR-M)*(Current Smoker)			-1.360*		
			(0.773)		
Age	0.328***	0.336***	0.333***	0.0371	0.407***
	(0.0423)	(0.0431)	(0.0431)	(0.130)	(0.0451)
Age Squared	-0.00309***	-0.00322***	-0.00319***	-0.000588	-0.00385***
	(0.000419)	(0.000430)	(0.000430)	(0.00134)	(0.000452)
Female	-0.204	-0.240	-0.245	0.888	-0.450
	(0.263)	(0.263)	(0.263)	(0.628)	(0.288)
Highest Qualification					
Bachelor degree or higher			(Base Group)		
Certificate/Diploma (>1FTE)	1.134***	1.184***	1.216***	0.303	1.197***
	(0.413)	(0.414)	(0.415)	(1.133)	(0.451)
Certificate/Diploma (≤1FTE)	1.007**	1.064**	1.056**	0.497	0.940*
	(0.452)	(0.453)	(0.454)	(1.135)	(0.484)
Trade/Apprenticeship	1.852***	1.936***	1.945***	1.375	1.912***
	(0.449)	(0.451)	(0.451)	(1.068)	(0.497)
Left school after 15, still studying	1.817**	1.933**	1.967**	0.927	2.275**
	(0.795)	(0.797)	(0.796)	(1.707)	(0.930)
Left school after 15	1.212***	1.286***	1.299***	0.115	1.404***
	(0.401)	(0.400)	(0.401)	(1.055)	(0.435)
Left school at 15 or less	1.431***	1.582***	1.574***	-0.0575	1.737***
	(0.554)	(0.557)	(0.558)	(1.121)	(0.644)
Still at school	-0.0801	-0.172	-0.240	-1.324	0.535
	(0.911)	(0.908)	(0.917)	(1.259)	(0.938)
Household Income Range					
≥ $100000			(Base Group)		
$80001-$100000	0.731*	0.753*	0.770*	-0.401	0.969**
	(0.419)	(0.420)	(0.420)	(1.045)	(0.460)
$60001-$80000	1.083**	1.117**	1.128**	-0.341	1.308***
	(0.442)	(0.443)	(0.443)	(1.101)	(0.487)
$50001-$60000	0.181	0.246	0.248	0.595	0.167
	(0.464)	(0.467)	(0.467)	(1.116)	(0.519)
$40001-$50000	0.574	0.649	0.650	-0.345	0.865
	(0.557)	(0.557)	(0.557)	(1.242)	(0.618)
$30001-$40000	0.786	0.861*	0.875*	0.349	0.834
	(0.508)	(0.509)	(0.509)	(1.243)	(0.555)
$20001-$30000	0.738	0.812	0.820*	0.0885	0.881*
	(0.494)	(0.494)	(0.495)	(1.291)	(0.533)
$12001-$20000	1.575***	1.722***	1.742***	-0.975	2.354***
	(0.531)	(0.533)	(0.535)	(1.145)	(0.602)
≤ $12000	0.781	0.951	0.961	-0.601	1.483*
	(0.729)	(0.731)	(0.730)	(1.445)	(0.860)
Functional Health Literacy					
Adequate			(Base Group)		
At Risk (NVS)	-0.219	-0.186	-0.196	-0.780	-0.0905
	(0.332)	(0.332)	(0.332)	(0.733)	(0.375)
Inadequate (NVS)	0.185	0.219	0.223	1.680*	0.0374
	(0.398)	(0.398)	(0.398)	(0.972)	(0.434)
Constant	17.47***	17.43***	17.43***	25.71***	15.55***
	(1.072)	(1.078)	(1.077)	(3.122)	(1.141)
Observations	1868	1868	1868	315	1553
R-squared	0.065	0.068	0.069	0.040	0.093
AIC	11589.571	11586.022	11584.921	1962.844	9629.183
BIC	11711.29	11713.27	11717.7	2039.648	9746.838

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

effect on BMI as would be expected, however the estimated effect of discounting on BMI is not changed significantly by the addition of the smoking variable as was predicted.

Column (3) of Table 5.6 shows the regression estimates for a specification including both an indicator variable for smoking, and an interaction term of the smoking variable with the discounting variable. When the interaction term is added, the estimated coefficient on the discounting indicator rises, the coefficient on smoking status falls and becomes statistically insignificant, and the interaction term is negative and significant. In this specification, the coefficient on PDR-M is the estimated effect of a positive rate of discounting in the monetary domain on BMI *for non-smokers*. The estimated effect of discounting on BMI *for current smokers* is the addition of the PDR-M and the interaction term coefficient estimates. These almost perfectly cancel one another out, and the resulting estimated effect of 0.057 is not significantly different from zero (p-value: 0.931). This regression therefore shows evidence that the effect of discounting on body weight is only important for non-smokers, and that the mitigating influence of discounting for smokers operate in such a way that discounting has little effect on weight for current smokers.

Columns (4) and (5) look at this further, by estimating separate regressions for the subsamples of current smokers, and non-smokers. These show similarly that the sample of non-smokers has a higher estimated effect of discounting on BMI than the overall population, and that there is no significant effect of discounting on BMI for current smokers. Note that statistical significance is lost for most variables in Column (4) for the sample of current smokers partly due to the reduced sample size.

In the estimated models of probability of obesity in Table 5.7, the findings are quite similar to the linear regression results. Adding the smoking indicator variable in Column (2) does little to impact the estimated effect of discounting on obesity propensity, and here the smoking indicator variable is not statistically significant. Adding an interaction term in Column (3) reveals a larger effect of discounting on obesity propensity for non-smokers. It appears that the larger magnitude on the interaction coefficient relative to the discounting coefficient might mean the estimated effect of discounting on obesity propensity would be negative for smokers, however the effect of discounting for smokers is not statistically significant (p-value:0.291). The subsample regressions in Columns (4) and (5) reflect similar results, with the effect of discounting on obesity propensity being larger for non-smokers, and statistically insignificant for smokers. Although the estimate is not statistically significant, the negative sign on the estimated effect of discounting for smokers is interesting, since it would be reasonable to suggest that the effect of discounting on the quantity of smoking could outweigh the effect of discounting on obesity propensity for this subsample.[6]

5.3.3 Discounting as a Mitigating Factor in the Estimation of Smoking's Effect on Body Weight

The potential for intertemporal discounting to be a mitigating factor relevant in the estimation of the effect of smoking on body weight outcomes has pre-

[6]Like the linear regression models, the model selection AIC and BIC measures suggest opposite selections, although the magnitude of the differences in the values is small.

Table 5.7: Logit Regressions on Obesity (BMI$\geq$ 30), With and Without Smoking (Odds Ratios)

	(1) No Variables	(2) Smoking Indicator	(3) Interaction Term	(4) Smokers Only	(5) Non-Smokers Only
PDR-M	1.477***	1.488***	1.794***	0.748	1.776***
	(0.201)	(0.203)	(0.268)	(0.243)	(0.270)
Current Smoker		0.799	1.015		
		(0.127)	(0.180)		
(Current Smoker)*(PDR-M)			0.398***		
			(0.140)		
Age	1.124***	1.127***	1.125***	1.013	1.155***
	(0.0246)	(0.0250)	(0.0250)	(0.0518)	(0.0297)
Age Squared	0.999***	0.999***	0.999***	1.000	0.999***
	(0.000216)	(0.000221)	(0.000221)	(0.000548)	(0.000254)
Female	1.265**	1.253*	1.251*	1.608	1.196
	(0.151)	(0.149)	(0.150)	(0.466)	(0.160)
<u>Highest Qualification</u>					
Bachelor degree or higher			(Base Group)		
Certificate/Diploma (>1FTE)	1.935***	1.962***	2.008***	1.574	1.993***
	(0.399)	(0.405)	(0.417)	(1.021)	(0.443)
Certificate/Diploma ($\leq$1FTE)	1.482*	1.500*	1.488*	1.291	1.447
	(0.320)	(0.324)	(0.324)	(0.805)	(0.340)
Trade/Apprenticeship	1.960***	2.007***	2.030***	1.369	2.093***
	(0.426)	(0.438)	(0.444)	(0.890)	(0.491)
Left school after 15, still studying	2.200**	2.273***	2.327***	1.388	2.655***
	(0.685)	(0.708)	(0.728)	(1.068)	(0.938)
Left school after 15	1.825***	1.864***	1.881***	1.452	1.901***
	(0.350)	(0.359)	(0.365)	(0.824)	(0.399)
Left school at 15 or less	1.823***	1.901***	1.886***	1.507	1.883**
	(0.421)	(0.444)	(0.441)	(0.920)	(0.495)
Still at school	0.769	0.749	0.712		0.915
	(0.597)	(0.582)	(0.556)		(0.740)
<u>Household Income Range</u>					
$\geq$ \$100000			(Base Group)		
\$80001-\$100000	1.659**	1.674**	1.694**	1.796	1.709**
	(0.348)	(0.352)	(0.358)	(1.074)	(0.389)
\$60001-\$80000	1.327	1.342	1.352	1.405	1.334
	(0.273)	(0.277)	(0.280)	(0.808)	(0.299)
\$50001-\$60000	1.150	1.173	1.172	1.527	1.130
	(0.283)	(0.290)	(0.291)	(0.939)	(0.314)
\$40001-\$50000	1.321	1.351	1.352	0.974	1.485
	(0.323)	(0.331)	(0.332)	(0.626)	(0.395)
\$30001-\$40000	1.328	1.361	1.365	1.309	1.363
	(0.321)	(0.330)	(0.332)	(0.827)	(0.364)
\$20001-\$30000	1.678**	1.716**	1.726**	1.625	1.741**
	(0.382)	(0.392)	(0.396)	(0.978)	(0.434)
\$12001-\$20000	2.039***	2.134***	2.163***	1.437	2.427***
	(0.469)	(0.496)	(0.504)	(0.825)	(0.629)
$\leq$ \$12000	1.959**	2.060**	2.090**	1.306	2.507***
	(0.593)	(0.626)	(0.633)	(0.895)	(0.868)
<u>Functional Health Literacy</u>					
Adequate			(Base Group)		
At Risk (NVS)	1.057	1.067	1.061	0.821	1.118
	(0.149)	(0.151)	(0.151)	(0.275)	(0.177)
Inadequate (NVS)	1.237	1.251	1.255	1.493	1.225
	(0.203)	(0.205)	(0.206)	(0.544)	(0.225)
Constant	0.00805***	0.00795***	0.00779***	0.117*	0.00402***
	(0.00450)	(0.00446)	(0.00437)	(0.151)	(0.00262)
Observations	1868	1868	1868	314	1553
Log pseudolikelihood	-1001.898	-1000.820	-997.120	-173.590	-817.811
AIC	2047.796	2047.639	2042.241	389.180	1679.621
BIC	2169.514	2174.889	2175.024	467.917	1797.276

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

viously been suggested, and assessed, by Robb, Huston, and Finke (2008). Their indicator of intertemporal preference was an index based on demographics and behavioural indicators, while the measure used here is aimed to more directly assess discounting behaviour. They find that adding their variable for intertemporal preference to a multivariate linear model of BMI determination, increases the estimated smoking effect from -1.53 to -1.94.

Tables 5.8 and 5.9 below estimate the effect of smoking on body weight, using a model containing the same controls as in the earlier specifications, except excluding the indicator of intertemporal discounting. Column (1) of each table shows this regression, while columns (2) and (3) repeat results from previous tables for ease of comparison.

The first linear regression on BMI in Column (1) of Table 5.8 shows that smoking has a statistically negative association with BMI after controlling for other demographics, with a point estimate of a reduction in BMI by 0.774 units for current smokers compared to non-smokers. While the addition of a control for discounting in Column (2) increases the magnitude of the coefficient on smoking, as in Robb, Huston, and Finke (2008), the degree of the change in the analysis here is only very small, from -0.774 to -0.817. Column (3) adds an interaction term which allows the effect of smoking on BMI to differ by discounting status. The estimates here find that smoking is associated with a statistically insignificant reduction in BMI of 0.483 units for non-discounters (p-value:0.229), and is associated with a decrease in BMI of 1.843 units for discounters (p-value:0.006). This suggests that the effect of smoking on BMI is greater for those individuals who exhibit a positive rate

Table 5.8: Linear Regressions on BMI, The Effect of Smoking

	(1) No PDR-M	(2) PDR-M	(3) Interaction
Current Smoker	-0.774**	-0.817**	-0.483
	(0.349)	(0.350)	(0.401)
PDR-M		1.126***	1.417***
		(0.346)	(0.399)
(Current Smoker)*(PDR-M)			-1.360*
			(0.773)
Age	0.342***	0.336***	0.333***
	(0.0433)	(0.0431)	(0.0431)
Age Squared	-0.00332***	-0.00322***	-0.00319***
	(0.000433)	(0.000430)	(0.000430)
Female	-0.288	-0.240	-0.245
	(0.265)	(0.263)	(0.263)
Highest Qualification			
Bachelor degree or higher		(Base Group)	
Certificate/Diploma (>1FTE)	1.181***	1.184***	1.216***
	(0.417)	(0.414)	(0.415)
Certificate/Diploma ($\leq$1FTE)	1.056**	1.064**	1.056**
	(0.457)	(0.453)	(0.454)
Trade/Apprenticeship	1.896***	1.936***	1.945***
	(0.455)	(0.451)	(0.451)
Left school after 15, still studying	2.037**	1.933**	1.967**
	(0.792)	(0.797)	(0.796)
Left school after 15	1.262***	1.286***	1.299***
	(0.402)	(0.400)	(0.401)
Left school at 15 or less	1.542***	1.582***	1.574***
	(0.560)	(0.557)	(0.558)
Still at school	-0.0386	-0.172	-0.240
	(0.889)	(0.908)	(0.917)
Household Income Range			
$\geq$ $100000		(Base Group)	
$80001-$100000	0.758*	0.753*	0.770*
	(0.424)	(0.420)	(0.420)
$60001-$80000	1.145***	1.117**	1.128**
	(0.443)	(0.443)	(0.443)
$50001-$60000	0.255	0.246	0.248
	(0.468)	(0.467)	(0.467)
$40001-$50000	0.709	0.649	0.650
	(0.555)	(0.557)	(0.557)
$30001-$40000	0.910*	0.861*	0.875*
	(0.513)	(0.509)	(0.509)
$20001-$30000	0.913*	0.812	0.820*
	(0.499)	(0.494)	(0.495)
$12001-$20000	1.906***	1.722***	1.742***
	(0.536)	(0.533)	(0.535)
$\leq$ $12000	1.141	0.951	0.961
	(0.721)	(0.731)	(0.730)
Functional Health Literacy			
Adequate		(Base Group)	
At Risk (NVS)	-0.190	-0.186	-0.196
	(0.333)	(0.332)	(0.332)
Inadequate (NVS)	0.214	0.219	0.223
	(0.399)	(0.398)	(0.398)
Constant	17.61***	17.43***	17.43***
	(1.074)	(1.078)	(1.077)
Observations	1868	1868	1868
R-squared	0.061	0.068	0.069
AIC	11596.363	11586.022	11584.921
BIC	11718.08	11713.27	11717.7

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.9: Logit Regressions on Obesity (BMI$\geq$ 30), The Effect of Smoking (Odds Ratios)

	(1) No PDR-M	(2) PDR-M	(3) Interaction
Current Smoker	0.812	0.799	1.015
	(0.128)	(0.127)	(0.180)
PDR-M		1.488***	1.794***
		(0.203)	(0.268)
(Current Smoker)*(PDR-M)			0.398***
			(0.140)
Age	1.130***	1.127***	1.125***
	(0.0252)	(0.0250)	(0.0250)
Age Squared	0.999***	0.999***	0.999***
	(0.000222)	(0.000221)	(0.000221)
Female	1.231*	1.253*	1.251*
	(0.146)	(0.149)	(0.150)
Highest Qualification			
Bachelor degree or higher		(Base Group)	
Certificate/Diploma (>1FTE)	1.958***	1.962***	2.008***
	(0.404)	(0.405)	(0.417)
Certificate/Diploma ($\leq$1FTE)	1.495*	1.500*	1.488*
	(0.324)	(0.324)	(0.324)
Trade/Apprenticeship	1.979***	2.007***	2.030***
	(0.433)	(0.438)	(0.444)
Left school after 15, still studying	2.371***	2.273***	2.327***
	(0.729)	(0.708)	(0.728)
Left school after 15	1.844***	1.864***	1.881***
	(0.355)	(0.359)	(0.365)
Left school at 15 or less	1.875***	1.901***	1.886***
	(0.440)	(0.444)	(0.441)
Still at school	0.781	0.749	0.712
	(0.606)	(0.582)	(0.556)
Household Income Range			
$\geq$ \$100000		(Base Group)	
\$80001-\$100000	1.674**	1.674**	1.694**
	(0.352)	(0.352)	(0.358)
\$60001-\$80000	1.355	1.342	1.352
	(0.278)	(0.277)	(0.280)
\$50001-\$60000	1.167	1.173	1.172
	(0.288)	(0.290)	(0.291)
\$40001-\$50000	1.388	1.351	1.352
	(0.336)	(0.331)	(0.332)
\$30001-\$40000	1.386	1.361	1.365
	(0.336)	(0.330)	(0.332)
\$20001-\$30000	1.776**	1.716**	1.726**
	(0.407)	(0.392)	(0.396)
\$12001-\$20000	2.277***	2.134***	2.163***
	(0.527)	(0.496)	(0.504)
$\leq$ \$12000	2.187***	2.060**	2.090**
	(0.658)	(0.626)	(0.633)
Functional Health Literacy			
Adequate		(Base Group)	
At Risk (NVS)	1.068	1.067	1.061
	(0.151)	(0.151)	(0.151)
Inadequate (NVS)	1.251	1.251	1.255
	(0.205)	(0.205)	(0.206)
Constant	0.00846***	0.00795***	0.00779***
	(0.00473)	(0.00446)	(0.00437)
Observations	1868	1868	1868
Log Pseudolikelihood	-1004.958	-1000.820	-997.120
AIC	2053.916	2047.639	2042.241
BIC	2175.634	2174.889	2175.024

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

of monetary discounting.

In the logit regressions on an obesity indicator in Table 5.9, the estimates do not show the effect of being a current smoker on obesity propensity as being statistically different from zero in the first two columns. The inclusion of an interaction term in Column (3) provides estimates showing that the effect of smoking on the probability of being obese is not significant for non-discounters, but is has an odds ratio of 0.4036 for monetary discounters (p-value:0.004). It appears that the negative effect of current smoking on obesity propensity may only occur for the subsample of positive discounters in the monetary domain.

Similar to Robb, Huston, and Finke (2008), it has been found here that the inclusion of an intertemporal discounting indicator does change the results obtained for estimations of the effect of smoking on body mass outcomes. Furthermore, an additional discovery is that this effect may operate largely within the subsample of discounters, rather than non-discounters. This has practical importance, since it is well-known that weight gain is a particular problem for individuals as they quit smoking, and may discourage cessation (Filozof, Pinilla, and Fernndez-Cruz 2004). An intertemporal discounting indicator could thus be used as a screening tool for likelihood of being at risk of weight gain on cessation of smoking. The knowledge of this pathway may also help in the appropriate design of behavioural interventions to reduce weight gain after smoking cessation or to help the maintenance of smoking cessation.

5.4 Conclusion

This chapter built on the robust findings from Chapter 4 of this thesis of an association between intertemporal discounting and body weight outcomes, by analysing the potential role of smoking behaviour as an important variable in this relationship.

As a basis for this analysis it was important to first assess the independent relationship between discounting and smoking behaviours. The analysis in Section 5.2 found that there was strong evidence of a relationship between intertemporal discounting, as measured by a stated preference indicator, and smoking behaviour. In particular it was found that being a discounter was positively associated with both the probability of being a current smoker and a former smoker, relative to never smokers. This provides some evidence that discounting is predominantly a stable trait that can explain smoking behaviour, rather than the 'reverse causality' of smoking determining the discount rate. Estimation of a sequential model added evidence that discounting is a predictor of smoking commencement rather than smoking cessation. Discounting behaviour responses could therefore potentially be useful as a diagnostic tool to determine risk of smoking commencement, thereby allowing targetted interventions. Most importantly, this section provided the evidence necessary to educate the joint analysis of smoking, body weight and discounting.

Since a higher rate of discounting will independently lead to higher body weight, and increased likelihood and quantity of smoking, then the negative effect of smoking on body weight could bias the estimated effect of discounting on body weight downwards. A number of models were estimated that provided evidence that this indeed may be the case. Although controlling for current smoking in the model did not noticeably alter the estimated effect of discounting on body weight, the addition of an interaction term to allow the effect of discounting on body weight to differ between smokers and non-smokers revealed interesting results. The effect of discounting on body weight outcomes is not significant amongst smokers, probably due to the mediating effects through smoking quantity. The estimated effect of discounting on BMI for non-smokers was higher than the estimated effect from the pooled sample, since in the latter case the effect is moderated by the presence of smokers.

Looking at similar issues from an alternative perspective, Robb, Huston, and Finke (2008) have shown that discounting behaviour could change the estimated effect of smoking on body weight. This hypothesis was also addressed here, and there was some evidence found of this relationship. In particular, it was found that the effect of smoking on body weight may operate more strongly within the group of individuals who are discounters.

Chapter 6

System Estimations of Obesity and Health Behaviours

6.1 Introduction

Body weight outcomes are determined in a large part by modifiable health behaviours, in particular exercise and diet patterns. The analysis presented in Chapters 4 and 5 of this thesis abstracted from the particular lifestyle choice pathways that determine body weight outcomes, by considering a model based on demographics and relatively permanent traits. This chapter examines the separate roles of diet and exercise within the determination of body weight outcomes.

Many studies have investigated the relative importance of exercise and diet, with varying results. A clear problem that must be faced when attempting to estimate the effect of health behaviour choices on body weight outcomes is the likelihood of there being unobserved factors that influence both lifestyle behaviours and body weight outcomes, which results in inconsistent estimates using many standard techniques due to an endogeneity problem. The problems can also to lead to inconsistent estimates of the effects of other explanatory variables on obesity, such as income and education.

In this chapter, a Multivariate Probit (MVP) model is used to specify a system of equations for behaviours and outcomes which resolves the endogeneity problems by allowing correlation of the error terms in each equation. This recursive system of equations is estimated using Maximum Simulated Likelihood (MSL). Evidence is found of correlation between the error terms of several of the equations, supporting the usage of the the MVP system estimation over a series of single-equation probit models. There is also a noticeable difference in the estimated partial effects of the health behaviours on the propensity of obesity depending on which methodology is used.

Previous chapters have discussed and analysed the importance of intertemporal discounting in the determination of health behaviours and outcomes. 'Planning' is a distinct concept, but one that is quite closely related to discounting. Some extensions of the multivariate probit systems estimations are presented that incorporate an indicator of each individual's degree of 'planning' in the model. The incorporation of this variable does not seem to alter the estimates of other parameters of the model noticeably. However this section does provide some insights into the pathways through which degree of planning impacts obesity outcomes.

6.2 Background

6.2.1 The Etiology of Obesity: Diet or Exercise?

Due to the complexity of body weight determination, it is difficult to analyse the etiology of obesity, meaning its causal determinants. There are three main factors that are believed to be the predominant causes of obesity: metabolic factors, diet, and physical inactivity, each of which can be affected by genetic components (Weisner et al. 1998). This assumption is based on an energy balance understanding of body weight change. Energy balance, the difference between energy intake and energy expenditure, must be a determinant of changing body weight, since energy cannot be created or destroyed (Schoeller 2008).

The relative importance of diet and exercise in the determination of body weight outcomes has always been of great interest, especially due to the obesity 'epidemic' of recent years. Clearly the relative importance of genetic and metabolic factors are also of great interest, but as the key behavioural choice variables, diet and exercise are an important focus for many, including policy makers and the designers of behavioural interventions. The issue of the relative importance of diet and exercise has been investigated by studies such as Prentice and Jebb (1995), Weisner et al. 1998, Stubbs and Lee (2004) and Bleich, Cutler, Murray, and Adams (2008).

Conflicting views about the relative importance of diet and exercise have been expressed in the literature, partly reflecting different methodologies, and also different distinct research questions. Prentice and Jebb (1995) use a time-series analysis approach, suggesting that data showing that energy intake may have decreased over several decades in Britain, while exercise levels have fallen, suggest that the blame for the obesity epidemic may fall predominantly on exercise. The results of this study, and other similar studies, are criticised by Stubbs and Lee (2004), who suggest caution in the interpretation of the data. Using a more robust statistical approach, Ng et al. (2010) find evidence that in China physical activity can explain almost double the weight gain that can be explained by diet.

It has been suggested that one of the major pitfalls of analysing survey data regarding both food intake and exercise is the potential for misreporting. It is possible with the use of 'doubly labeled water'[1] to accurately

[1]This method uses water with uncommon isotopes of either hydrogen or oxygen in

measure individuals' total energy expenditure (Schoeller 2008). Recent studies using this methodology have found that increasing body weight is associated with increased energy expenditures, suggesting the importance of energy intake rather than energy expenditure as a determinant of increased weight (Stunkard et al. 1999). However, these results are asking a quite different question to the importance of diet versus exercise, as energy expenditure is clearly not synonymous with exercise. Higher body weights are associated with higher resting energy expenditures, so further controls need to be incorporated to answer questions with respect to exercise. One study that used the doubly label water method to analyse energy balance, but also controlled for physical activity is Tataranni et al. (2003), which found that energy intake was significantly associated with body weight, but baseline energy expenditure due to physical activity was not.

There are also recent studies using a more epidemiological approach that suggest that diet may be more important than exercise, such as Bleich et al. (2008), and Goris and Westerterp (2008). Clearly there is still much debate about the relative importance of diet and exercise in the etiology of obesity.

The estimated models in this chapter, as well as looking at diet and exercise as determinants of obesity, will also incorporate the association between obesity and other risk factors, such as income, education, and other demographics. Background literature relating to these is included in Section 2.7 of this thesis.

order to track chemical reactions.

6.2.2 Multivariate Probit Systems Estimation of Health Behaviours and Outcomes

The key difficulty regarding estimation of the determinants of body weight outcomes including diet and exercise variables is the endogeneity of these choice variables. The approach taken to deal with this problem in this chapter is by simultaneously estimating a recursive system of equations for obesity, and lifestyle choices. Since these dependent variables used are binary, the probit methodology is used, so the system is a Multivariate Probit (MVP) system of equations.

The use of the modern methodology of estimating MVP systems of equations using Maximum Simulated Likelihood (MSL) in the context of health, was pioneered by Contoyannis and Jones (2004). They estimate a recursive system of equations for self assessed health and health-related lifestyle variables. While they recognise that it is not technically a lifestyle, the authors make the decision to include obesity as one of the 'lifestyle' variables that affects self assessed health. Although it contains similar variables, the model there is quite different to the one that is presented in this chapter. After controlling for a vector of other covariates, they estimate a significant correlation of the error term for equations for exercise status and obesity status ($\rho = 0.29$), but this result may be quite different to the results presented in this chapter due to vast differences in the model; in particular the fact that exercise is not directly present in the obesity equation. Using a similar approach, Balia and Jones (2008) estimate a recursive system of equation for lifestyles, self assessed health status, and mortality. Once again obesity is included as a 'lifestyle' variable; the correlation coefficients are significant between the obesity indicator, and indicators of mortality, self assessed health, smoking, eating breakfast, and exercise. The technique of MSL estimation of MVP systems has also been used in other recent health-related publications including Park and Kang (2008), Zhang, Zhao, and Harris (2009), and Harris et al. (2009).

6.3 Empirical Model and Estimation Procedures

The proposed model is intended to be an estimable model of the propensity to be obese. The focus is on obesity rather than alternative measures of body weight outcomes, due to the particular clinical and epidemiological relevance of obesity. A structural model of the probability of obesity is adopted that depends on the health behaviours of diet and exercise, as well as observable individual factors such as sex, age and ethnicity, and unobservable factors. The assumption of these direct relationships for the obesity equation is reasonable, since for example it is well accepted that the more you exercise, the less likely you are to be obese. However, there are no such known direct causal mechanisms by which individual characteristics affect the key health behaviours: diet and exercise. For this reason it is necessary to use reduced-form equations for the health behaviours that include a number of variables that may jointly determine these lifestyle choices such as sex, age, income, education, and marital status.

An individual is either obese or not obese. Let these statuses be denoted by $O = 1$ and $O = 0$ respectively. A unobserved latent variable can be defined, where a latent variable $O^* \in (-\infty, \infty)$ is mapped to the discrete outcome as follows.

$$O = \begin{cases} 1 & \text{if } O^* > 0 \\ 0 & \text{if } O^* \leq 0 \end{cases} \tag{6.1}$$

The latent variable is assumed to depend on exercise and diet, which are determined endogenously in the model, a vector of exogenous explanatory variables X_O, and an error term ε_O. Based on the available data, exercise is modelled by an indicator variable for if the individual is sedentary or does some exercise, (L_E), and diet is modelled using indicators of fruit consumption (L_F) and vegetable consumption (L_V).

$$O^* = \alpha_E L_E + \alpha_F L_F + \alpha_V L_V + X_O' \beta_O + \varepsilon_O \tag{6.2}$$

Reduced form specifications for the lifestyle equations for exercise and diet are modelled as follows.

$$L_E^* = X_E' \beta_E + \varepsilon_E \tag{6.3}$$

$$L_F^* = X_F' \beta_F + \varepsilon_F \tag{6.4}$$

$$L_V^* = X_V' \beta_V + \varepsilon_V \tag{6.5}$$

These equations determine unobserved latent variables that correspond to the propensity to exhibit the corresponding choice. The latent variables are mapped to the discrete outcomes in the usual way.

$$L_j = \begin{cases} 1 & \text{if } L_j^* > 0 \\ 0 & \text{if } L_j^* \leq 0 \end{cases} \tag{6.6}$$

Where $j = E, F$ and V.

The empirical implementation of this model will estimate the α and β coefficients, and from these coefficients estimated effects of variables on the probability of obesity will be derived.

If it was assumed that the error terms of the above four equations were uncorrelated, then each equation could be separately estimated using a standard technique, such as univariate probit estimation. This will be done as a comparator case.

However, if the error terms are correlated with one another, due to unobservable individual characteristics that affect multiple dependent variables, then estimation of the obesity equation will be inconsistent due to an endogeneity problem. It may be possible to avoid the endogeneity problem by allowing the error terms of the four equations to be correlated, using multivariate probit system estimation.

For this approach, it is assumed that the error terms follow a multivariate normal distribution. In other words, $(\varepsilon_O, \varepsilon_E, \varepsilon_F, \varepsilon_V) \sim MVN(0, \Sigma)$, where

$$\Sigma = \begin{bmatrix} 1 & \rho_{OE} & \rho_{OF} & \rho_{OV} \\ \rho_{OE} & 1 & \rho_{EF} & \rho_{EV} \\ \rho_{OF} & \rho_{EF} & 1 & \rho_{FV} \\ \rho_{OV} & \rho_{EV} & \rho_{FV} & 1 \end{bmatrix} \tag{6.7}$$

The ρ terms give the correlation between the error terms of the equations for obesity and health behaviours. If these ρ's are all zero, then there is no need to use the MVP estimation method as a series of univariate probit estimations will produce consistent parameter estimates. However, if there are no zero ρ's, then the univariate approach will not produce consistent coefficient estimates, and the MVP approach should be used (Maddala 1983).

The system cannot be estimated by full information maximum likelihood (FIML), since there are integrals in the likelihood function with no closed form. As such the model will be estimated using a Maximum Simulated Likelihood (MSL) technique, using the Geweke-Hajivassiliou-Keane (GHK) simulator for evaluating the multivariate normal distribution functions. Operationally, the estimations use the *mvprobit* command in Stata 10, which was written by and is more fully described by Cappellari and Jenkins (2003).

Maddala (1983) emphasises the need for exclusion restrictions for identification. However, Wilde (2000) shows that as long as there is sufficient variation in the exogenous regressors, then exclusion restrictions are not necessary for the identification of a MVP model. Specifications will be estimated both without exclusion restrictions, and with exclusion restrictions that are based on appropriate theory.

6.4 Data

The dataset used in this chapter is the North West Adelaide Health Study (NWAHS). The NWAHS is a longitudinal cohort study of a representative population of adults in the north west of Adelaide, that commenced in the year 2000 and is continuing at present. The dataset contains both clinically collected and survey collected data, covering a wide range of medical, lifestyle and demographic variables. At the time this analysis was undertaken there had been two main phases of data collection, with some between-phase telephone and postal survey follow-ups. There were 4060 participants in the first stage of the study, but due to non-response in later data collections the sample size is reduced.

The sample size that is used in this chapter's data analysis is 943 individual respondents. The sample includes all 'baby boomer'[2] respondents who are not yet retired and who participated in a particular telephone follow-up survey in 2007, excluding those who have missing values for any of the variables in the analysis. The sample for analysis is restricted to baby boomers who are not retired since a particular question on 'planning' for retirement is only available for those respondents. An additional benefit is that this will also potentially eliminate differences between diverse age groups and generational cohorts that are not captured by the variables for age. While the restriction to baby boomers is only necessary for the analysis in the subsection in 'planning', the restriction has also been put in place for the other analysis for the sake of consistency.

Variable descriptions and summary statistics are shown in Appendix B.

[2]'Baby boomer' is defined here as persons born between 1946 and 1965, inclusive.

6.5 Data Analysis and Estimation Results

6.5.1 Descriptive Analysis

The association between obesity and lifestyle variables representing diet and exercise is a key topic of interest. It may be useful to undertake some preliminary analysis of these associations without conditioning on other variables.

Pearson χ^2 tests were undertaken to test whether obesity status is related to or is independent of each lifestyle variable. The results are presented below in Table 6.1. The χ^2 tests show evidence that without conditioning on other variables, there is strong evidence of a relationship between exercise and obesity, but no significant evidence of a relationship between either of the dietary indicators and obesity.

Table 6.1: χ^2 Tests of Independence of Obesity and Each Lifestyle Indicator

	χ^2	p-value
Exercise	15.5842	0.000
Fruit	2.3079	0.129
Vegetable	0.0706	0.790

Looking at the partial correlation of each of the lifestyle variables with the obesity status indicator, a similar outcome is evident. The partial correlation measures the degree of linear association between each lifestyle variable and obesity, holding the other two remaining lifestyle variables fixed. Table 6.2 shows these figures. There is a significant negative partial correlation between exercise and obesity, holding dietary indicators fixed, as should be expected. However the dietary indicators do not show significant correlation with obesity at any standard significance level. However these simple descriptive statistics do not take into account other important explanatory variables such as sex and age, and so these results are preliminary, and do not necessarily suggest associations will not be evident using more appropriate econometric techniques.

Table 6.2: Partial Correlations of Lifestyle Variables with Obesity

	Correlation	Significance
Exercise	-0.1251	0.000
Fruit	-0.0404	0.216
Vegetable	0.0200	0.541

6.5.2 Single Equation Probit Estimation

Under the assumption of all ρ terms in Equation 6.7 being zero, meaning there is no correlation between the error terms of the equations, it would be appropriate to estimate each probit equation separately. Although there is reason to believe a MVP system approach to the estimate may be necessary, this naive single equation approach is presented here as the standard baseline, to which MVP results will be contrasted.

First, the equation for obesity is estimated, which depends on the three lifestyle variables, as well as a vector of regressors X'_O. As discussed earlier, a model with exclusion restrictions and without exclusion restrictions will be tested, what this means is models with different variables in the vector X'_O. The model without exclusion restrictions includes all variables introduced in Section 6.4, except 'planning' which will be introduced later. The model with exclusion restrictions includes only variables for age, sex, and country of birth in X'_O, to control for biological characteristics, and assumes that the effects of all other demographic variables occur only through diet and exercise. Throughout the next sections the restricted and unrestricted model refer to models whether the vector X'_O differ in these ways. In all models for the lifestyle variables the full set of regressors (aside from 'planning') are included in X'_E, X'_F and X'_V.

Coefficient estimates for univariate probit models of obesity are shown in Table 6.3 for the restricted and unrestricted models. In both cases the exercise variable has a statistically significant association with the probability of obesity in the expected direction, while the diet variables are not significant. This is the case whether the full set of demographic characteristics are controlled for or not.

In the restricted model, the other variables that are significant are age and one of the country of birth indicators. These show evidence of a positive association between age and the probability of being obese, and a negative association between being born in the UK or Ireland and obesity probability (relative to being Australian born). In the unrestricted model notable significant variables are some indicating lower incomes are positively associated with probability of being obese, as is being 'never married'.

RESET tests of model misspecification were carried out on both models, and there is no significant evidence of model misspecification in either case[3].

[3]For the restricted model the χ^2 value is 1.13, with a p-value of 0.2881. For the unrestricted model the χ^2 value is 0.52, with a p-value of 0.4691

Table 6.3: Single Equation Probit Estimates for Obesity

	(1) Restricted		(2) Unrestricted	
	Coefficient	Std.Err.	Coefficient	Std.Err.
Exercise	-0.359***	(0.0929)	-0.311***	(0.0979)
Vegetable	0.0248	(0.0888)	0.0507	(0.0918)
Fruit	-0.0973	(0.0900)	-0.0809	(0.0938)
Age	0.0150*	(0.00784)	0.0168**	(0.00826)
Female	0.0234	(0.0886)	-0.0393	(0.108)
COB2	-0.332***	(0.125)	-0.314**	(0.129)
COB3	-0.289	(0.246)	-0.222	(0.251)
COB4	-0.292	(0.248)	-0.257	(0.256)
COB7	-0.146	(0.298)	-0.353	(0.322)
EDN2			0.142	(0.161)
EDN3			0.0349	(0.195)
EDN4			0.171	(0.171)
EDN5			-0.207	(0.192)
Income1			0.486	(0.301)
Income2			0.763***	(0.251)
Income3			0.368*	(0.197)
Income4			0.201	(0.174)
Income5			0.309*	(0.168)
Income6			0.355**	(0.160)
Income7			0.275*	(0.144)
Marital2			0.0104	(0.133)
Marital3			-0.611*	(0.350)
Marital4			0.439***	(0.161)
Work2			-0.102	(0.119)
Work3			-0.377	(0.297)
Work4			0.219	(0.191)
Work5			0.283	(0.440)
Work6			0.0154	(0.646)
Work7			-0.666*	(0.399)
Constant	-0.838**	(0.389)	-1.293***	(0.458)
Observations	918		918	
Log Pseudolikelihood	-566.22667		-543.76077	
AIC	1152.453		1147.522	
BIC	1200.675		1292.187	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.4: Single Equation Probit Estimates for Lifestyle Variables

	(1) Exercise		(2) Fruit		(3) Vegetable	
	Coefficient	Std.Err.	Coefficient	Std.Err.	Coefficient	Std.Err.
Age	0.00199	(0.00819)	0.0197**	(0.00809)	0.0124	(0.00795)
Female	0.0616	(0.104)	0.297***	(0.0986)	0.347***	(0.0996)
COB2	-0.151	(0.122)	-0.120	(0.119)	-0.133	(0.119)
COB3	-0.365	(0.223)	-0.00470	(0.231)	-0.0846	(0.228)
COB4	-0.408	(0.255)	0.188	(0.229)	-0.217	(0.239)
COB5	-0.288	(0.430)	1.055**	(0.498)	-0.188	(0.395)
COB6	0.0644	(0.383)	0.359	(0.356)	-0.548	(0.393)
COB7	0.241	(0.299)	-0.253	(0.290)	-0.233	(0.292)
EDN2	0.257*	(0.155)	0.197	(0.161)	0.217	(0.159)
EDN3	0.746***	(0.190)	0.254	(0.192)	0.307	(0.189)
EDN4	0.655***	(0.165)	0.303*	(0.170)	0.185	(0.168)
EDN5	0.795***	(0.183)	0.675***	(0.185)	0.419**	(0.182)
Income1	-0.242	(0.302)	0.285	(0.295)	0.0363	(0.282)
Income2	-0.462*	(0.250)	0.400	(0.243)	-0.0975	(0.244)
Income3	-0.557***	(0.193)	-0.0529	(0.191)	0.0738	(0.188)
Income4	-0.297*	(0.171)	0.0419	(0.168)	0.0569	(0.166)
Income5	-0.275*	(0.162)	0.284*	(0.156)	-0.0930	(0.155)
Income6	-0.149	(0.163)	-0.0921	(0.152)	-0.103	(0.148)
Income7	-0.255*	(0.142)	0.236*	(0.134)	-0.0595	(0.132)
Marital2	0.0546	(0.134)	-0.174	(0.132)	-0.343***	(0.130)
Marital3	0.581	(0.401)	-0.0501	(0.301)	-0.470	(0.334)
Marital4	0.106	(0.168)	0.0225	(0.163)	-0.262	(0.161)
Work2	-0.0349	(0.118)	-0.174	(0.112)	0.168	(0.112)
Work3	0.430	(0.303)	-0.586*	(0.305)	0.405	(0.288)
Work4	0.296	(0.187)	-0.377**	(0.184)	0.0206	(0.176)
Work5	0.169	(0.387)	-0.0339	(0.375)	0.770*	(0.394)
Work6	0.286	(0.742)				
Work7	0.738*	(0.433)	-1.050***	(0.395)	-0.223	(0.362)
Constant	0.110	(0.445)	-1.596***	(0.446)	-1.087**	(0.437)
Observations	943		939		939	
Log Pseudolikelihood	-548.96717		-603.8572		-618.94158	
AIC	1155.934		1263.714		1293.883	
BIC	1296.557		1399.369		1429.538	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The models are compared using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

$$\text{AIC} = -2logL + 2q \tag{6.8}$$

$$\text{BIC} = -2logL + qlogN \tag{6.9}$$

Where q is the number of parameters in the model, N is the number of observations, and L is the maximised value of the likelihood function. Lower values of the AIC or BIC correspond to support for that model according to that criterion. According to the BIC there is strong support for the restricted model, while the AIC suggests the unrestricted model is preferred. Both specifications will be tested further in the Multivariate Probit analysis to follow.

Table 6.4 shows single equation probit estimations for each of the lifestyle variables, as a potential comparison to the MVP system estimates in the following section.

6.5.3 Multivariate Probit System Estimation

As described in Section 6.3, Maximum Simulated Likelihood is used to estimate a Multivariate Probit System of equations. Coefficient estimates for these models are presented in Table 6.5 for the model with exclusion restrictions, and in Table 6.6 for the model without exclusion restrictions.

Both the AIC and BIC favour the model with exclusion restrictions over the model without exclusion restrictions. This model is also preferable on

Table 6.5: MVP System Estimation: With Exclusion Restrictions

	Obese	(Std.Err.)	Exercise	(Std.Err.)	Fruit	(Std.Err.)	Vegetable	(Std.Err.)
Exercise	-0.710**	(0.327)						
Vegetable	-1.111***	(0.218)						
Fruit	-0.327	(0.333)						
Age	0.0161**	(0.00730)	0.00163	(0.00836)	0.0189**	(0.00805)	0.00939	(0.00784)
Female	0.191**	(0.0906)	0.0733	(0.103)	0.299***	(0.0997)	0.360***	(0.0941)
COB2	-0.334***	(0.112)	-0.147	(0.125)	-0.132	(0.122)	-0.153	(0.117)
COB3	-0.268	(0.215)	-0.341	(0.238)	-0.00225	(0.229)	-0.0772	(0.219)
COB4	-0.324	(0.223)	-0.393*	(0.237)	0.186	(0.238)	-0.191	(0.234)
COB5	-1.901	(2.568)	-0.314	(0.416)	1.044**	(0.476)	-0.315	(0.393)
COB6	-4.680	(119.8)	0.102	(0.366)	0.390	(0.347)	-0.467	(0.369)
COB7	-0.194	(0.271)	0.294	(0.326)	-0.233	(0.301)	-0.187	(0.297)
EDN2			0.203	(0.156)	0.142	(0.166)	0.0394	(0.139)
EDN3			0.675***	(0.194)	0.192	(0.196)	0.121	(0.166)
EDN4			0.571***	(0.176)	0.232	(0.177)	-0.0147	(0.147)
EDN5			0.743***	(0.188)	0.625***	(0.187)	0.272*	(0.164)
Income1			-0.297	(0.300)	0.205	(0.294)	-0.152	(0.246)
Income2			-0.554**	(0.252)	0.287	(0.258)	-0.354*	(0.207)
Income3			-0.597***	(0.188)	-0.0962	(0.189)	-0.0323	(0.165)
Income4			-0.320*	(0.167)	0.0160	(0.165)	0.0127	(0.139)
Income5			-0.293*	(0.159)	0.252	(0.155)	-0.172	(0.133)
Income6			-0.172	(0.155)	-0.135	(0.149)	-0.177	(0.125)
Income7			-0.266*	(0.139)	0.200	(0.135)	-0.141	(0.114)
Marital2			0.0967	(0.132)	-0.127	(0.135)	-0.218*	(0.126)
Marital3			0.700*	(0.360)	0.0667	(0.329)	-0.156	(0.287)
Marital4			0.0526	(0.170)	-0.0133	(0.159)	-0.351**	(0.140)
Work2			-0.0308	(0.114)	-0.170	(0.111)	0.168*	(0.0951)
Work3			0.489	(0.330)	-0.603*	(0.310)	0.455*	(0.247)
Work4			0.249	(0.191)	-0.414**	(0.182)	-0.0865	(0.152)
Work5			0.0832	(0.430)	-0.146	(0.416)	0.502	(0.374)
Work6			0.390	(0.651)	-6.054	(2,333)	-5.621	(4,257)
Work7			0.865*	(0.442)	-0.973**	(0.432)	0.0383	(0.324)
Constant	-0.0401	(0.401)	0.188	(0.455)	-1.476***	(0.453)	-0.719*	(0.424)
Observations	943		AIC	4844.5821		BIC	5353.7341	

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6.6: MVP System Estimation: Without Exclusion Restrictions

	Obese	(Std.Err.)	Exercise	(Std.Err.)	Fruit	(Std.Err.)	Vegetable	(Std.Err.)
Exercise	0.160	(0.569)						
Vegetable	0.545	(0.611)						
Fruit	0.584	(0.678)						
Age	0.00734	(0.0100)	0.00167	(0.00842)	0.0202**	(0.00802)	0.0127	(0.00792)
Female	-0.185	(0.128)	0.0565	(0.104)	0.299***	(0.101)	0.352***	(0.0991)
COB2	-0.201	(0.136)	-0.152	(0.125)	-0.105	(0.121)	-0.130	(0.119)
COB3	-0.109	(0.244)	-0.375	(0.231)	-0.0240	(0.227)	-0.0972	(0.231)
COB4	-0.168	(0.281)	-0.407*	(0.235)	0.187	(0.241)	-0.209	(0.238)
COB5	-8.504	(0)	-0.262	(0.419)	1.108**	(0.468)	-0.170	(0.408)
COB6	-8.330	(0)	0.0377	(0.367)	0.335	(0.346)	-0.565	(0.364)
COB7	-0.244	(0.315)	0.224	(0.318)	-0.213	(0.300)	-0.219	(0.296)
EDN2	0.000277	(0.167)	0.250	(0.156)	0.207	(0.160)	0.211	(0.157)
EDN3	-0.202	(0.231)	0.739***	(0.191)	0.261	(0.191)	0.307	(0.187)
EDN4	-0.0542	(0.199)	0.660***	(0.168)	0.293*	(0.170)	0.172	(0.167)
EDN5	-0.539**	(0.218)	0.783***	(0.187)	0.670***	(0.182)	0.409**	(0.179)
Income1	0.398	(0.321)	-0.263	(0.306)	0.269	(0.291)	-0.00331	(0.288)
Income2	0.663**	(0.321)	-0.475*	(0.251)	0.392	(0.247)	-0.108	(0.245)
Income3	0.409*	(0.224)	-0.563***	(0.192)	-0.0538	(0.191)	0.0714	(0.185)
Income4	0.198	(0.186)	-0.304*	(0.174)	0.0460	(0.166)	0.0505	(0.163)
Income5	0.262	(0.211)	-0.287*	(0.165)	0.287*	(0.154)	-0.0911	(0.154)
Income6	0.374**	(0.152)	-0.160	(0.160)	-0.0847	(0.150)	-0.107	(0.149)
Income7	0.232	(0.182)	-0.264*	(0.144)	0.237*	(0.134)	-0.0600	(0.133)
Marital2	0.105	(0.148)	0.0606	(0.134)	-0.172	(0.132)	-0.335**	(0.132)
Marital3	-0.515	(0.415)	0.573	(0.356)	-0.0436	(0.325)	-0.468	(0.321)
Marital4	0.421**	(0.164)	0.0957	(0.169)	0.00550	(0.162)	-0.260	(0.159)
Work2	-0.0755	(0.133)	-0.0320	(0.116)	-0.158	(0.113)	0.177	(0.111)
Work3	-0.340	(0.375)	0.406	(0.321)	-0.547*	(0.317)	0.424	(0.279)
Work4	0.235	(0.226)	0.302	(0.190)	-0.377**	(0.186)	0.0251	(0.181)
Work5	0.0918	(0.455)	0.141	(0.427)	-0.0644	(0.408)	0.770*	(0.416)
Work6	0.543	(0.770)	0.304	(0.686)	-11.83	(0)	-9.085	(0)
Work7	-0.435	(0.517)	0.728*	(0.437)	-1.049**	(0.432)	-0.201	(0.372)
Constant	-1.355**	(0.602)	0.142	(0.460)	-1.630***	(0.443)	-1.099**	(0.434)
Observations	943		AIC	4854.6825		BIC	5460.8158	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

theoretical grounds, and on the grounds that it is less likely to have identification problems. As such the discussion will primarily focus on the model with exclusion restrictions, with the results of the model without exclusion restrictions also presented in tables for the interested reader.

The usage of the Multivariate Probit system estimation was based on the assumption that there are unobservable factors that influence multiple equations, which cause the error terms (ε's) to be correlated. In other words the assumption is that various ρ's in the error correlation matrix are non-zero. These ρ's are not imposed but are estimated by the maximum simulated likelihood estimation procedure. The estimated ρ's are shown in Table 6.7, along with indicators of statistical significance.

Looking first at the model with exclusion restrictions, there are a number of the ρ's are statistically different from zero. This supports the use of the MVP model, rather than a set of single equation probit estimations, which imposes that all off-centre correlation coefficients in the error correlation matrix are zero. A likelihood ratio test of the hypothesis that all ρ's are zero is rejected strongly (χ^2=41.4031, p-value=0.0000). There is strong evidence of correlation between the error terms in the fruit and vegetable equations, this is to be expected as it seems likely that *unobserved* factors that influence fruit consumption will also influence vegetable consumption in the same direction. Similarly there is strong evidence of correlation between the error terms of the exercise and fruit consumption equations, and the vegetable and obesity equations. There is also evidence of correlation between the error terms of the obesity and exercise equations. Results are similar in the model without exclusion restrictions.

Table 6.7: Correlation Coefficient Estimates from MSL Procedure

	Obese	Exercise	Fruit	Vegetable
With Exclusion Restrictions				
Obese	1.000			
Exercise	0.340*	1.000		
Fruit	0.306	0.145***	1.000	
Vegetables	0.783***	0.067	0.229***	1.000
Without Exclusion Restrictions				
Obese	1.000			
Exercise	0.153	1.000		
Fruit	-0.221	0.162***	1.000	
Vegetables	0.803***	0.069	0.225***	1.000

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

The model with exclusion restrictions finds significant evidence of the expected negative relationships between both exercise and vegetable consumption and the probability of being obese. The coefficient on the other diet variable, fruit consumption, is in the expected negative direction but is not statistically significant. This is in contrast to the univariate probit estimation results, which did not find a significant association between either diet variable and obesity. Age, sex and a country-of-birth dummy are also significant.

6.5.4 Comparison of Average Partial Effect Estimates

While which variables are statistically significant is important, a matter of perhaps even greater interest is the magnitude of the estimates, particular of the key variables. Table 6.8 shows the estimated 'average partial effects' for the lifestyle variables in the multivariate probit model with exclusion restrictions, the multivariate probit model without exclusion restrictions, the univariate probit model with exclusion restrictions, and the univariate model without exclusion restrictions. This shows how the estimates of the partial effect of diet and exercise on obesity vary across the different estimation procedures. The average partial effects are calculated by calculating the estimated partial effect of each variable on the probability of obesity for each individual, then averaging across all individuals in the sample.

Table 6.8: Estimates of Average Partial Effect on Obesity Propensity

	Probit (Exclusions)	Probit (NoExclusions)	MVP (Exclusions)	MVP (NoExclusions)
Exercise	-0.131	-0.108	-0.227	0.051
	(0.009)	(0.016)	(0.054)	(0.014)
Vegetable	0.009	0.017	-0.355	0.180
	(0.001)	(0.003)	(0.075)	(0.043)
Fruit	-0.034	-0.027	-0.100	0.195
	(0.003)	(0.005)	(0.032)	(0.046)

Standard deviations are shown in parentheses.

In the univariate probit model, whether the simpler model with exclusion restrictions, or the larger model the controlled for many more covariates, the coefficients on the two dietary variables were not significantly different from zero. However the exercise variable was significantly negatively associated with obesity. The magnitude of this estimated effect on the probability, as shown in Table 6.8, was 13.1% for the model with exclusion restrictions, and 10.8% for the model without exclusion restrictions. This means that the average estimated effect of being an exerciser, rather than being sedentary, on the probability of being obese was to reduce the probability by 13.1% (or 10.8% depending on the model selected). If only standard probit analysis was undertaken, then a researcher might have concluded that the data shows no effect of diet on the probability of being obese, and shows that exercise reduces the probability by around 10%.

Appropriately allowing for the existence of unobservables that affect obesity, exercise and diet choices, by allowing the error terms of the equations for each variable to be correlated, leads to results that are quite different. The unusual results for the multivariate probit estimation with no exclusion restrictions should probably be ignored, since none of the three determinants of obesity is significant in the model, due to poor identification. So focusing on the multivariate probit model with exclusion restrictions, the results are quite different to the univariate results.

Firstly, all three of the variables for exercise and diet are statistically significantly associated with obesity propensity in the expected direction (that it, negatively). This is in stark contrast to the univariate probit model that seemed to put all the emphasis on exercise rather than diet as a determinant of obesity. All three variables are also much more significant determinants in a quantitative sense. Being an exerciser, rather than being sedentary, is now estimated to reduce the probability of being obese by 22.7% on average. This average effect is almost double that estimated by the simpler univariate probit model. Vegetable consumption, which was not even significant in the univariate probit model, is now estimated to be associated with a 35.5%

reduction on average in the probability of obesity. The average partial effect of fruit meanwhile is estimated to be a reduction in obesity probability of 10%. These results are much more believable than those derived from the univariate probit estimations, as the role of diet and exercise in body weight determination is well accepted.

The above results provide interesting estimates of the partial association between health behaviours and obesity propensity. Moreover, the results show the distinctly different results that can be obtained from using a multivariate probit system model, rather than a naive univariate probit model.

6.6 An Extension: Incorporating 'Planning'

The preceding chapters have looked at the association between a stated-choice indicator of intertemporal discounting and body weight outcomes. Here in contrast a variable is used to indicate the degree of planning for retirement that the respondent states they have undertaken. This concept is distinct yet related to concepts of intertemporal discounting.

The goal here is not to compare the indicators of discounting used in previous chapters to this measure of planning. Since these variables are contained in different data sets it is difficult to directly make comparisons. Moreover, the methodology used in this chapter is different to that of previous chapters, in part due to the different data, and this is another reason why direct comparisons cannot be made.

Borghans and Golsteyn (2006) look for associations between BMI and a battery of indicators of intertemporal discounting, including an elicited discount rate measure, and a question based on degree of planning. Using linear regression, they find that their 'planning' variable is statistically significantly associated with BMI, but their discount rate is not. This result of course depends on the particular explanatory variables controlled for, and the methodologies used. Based on the results of the earlier chapters of this thesis it seems that discarding the discounting indicator as an important explanatory variable in favour of a planning indicator may be inappropriate. Nevertheless, these previous results do suggest that there may be interesting information within a stated-choice indicator of planning that are worthy of further analysis.

The specific variable that will be used in the following analysis is an indicator variable taking the value '1' if the respondent has undertaken some planning for retirement prior to retirement. The sample used is entirely baby boomers who are not yet retired. Individuals were coded as having undertaken planning if they stated either that they were 'already thinking about it or planning for it', or if they stated they were not going to retire[4].

There are several main objectives of this section. One result of interest, will be assessing how controlling for 'planning' affects the estimates of the other parameters of the model. The other main objective is to assess how the effect of 'planning' is best modelled within the system of relationships. For example, one would expect the effect of planning on obesity propensity

[4]Stating definitively that they were not going to retire was considered evidence of having given significant thought to retirement

to operate through diet and exercise choices, and thus for there to be little association between obesity and planning once the health behaviours are controlled for.

Planning may be an important determinant of obesity, diet and exercise, that was unobserved in the previous specifications. So although evidence was shown previously of the validity of using a MVP model rather than a single equation model, this cannot necessarily be taken for granted in this different specification. First, consider the inclusion of the planning indicator in the single equation probit models for obesity, both restricted and unrestricted. These results are shown in Table 6.9. In the restricted model, being a planner has a negative impact on the probability of being obese, but it is not significant in the unrestricted model. Comparing Table 6.9 to Table 6.3, the estimates of other coefficients do not seem to be greatly affected by the inclusion of the planning indicator.

Single equation probit models were also estimated for the health lifestyle behaviours, with the addition of planning as an explanatory variable. These estimation results are shown in Table 6.10. They show the planning indicator to be significantly positively associated with exercise and vegetable consumption.

A multivariate probit system is estimated using maximum simulated likelihood that is identical to the model with exclusion restrictions previously estimated, but including 'planning' as an exogenous explanatory variable for diet and exercise (Table 6.11). Like in the univariate probit models, planning is found to be statistically significantly associated with exercise and vegetable

Table 6.9: Single Equation Probit Estimates for Obesity; Including Planning

	(1) Restricted		(2) Unrestricted	
	Coefficient	Std.Err.	Coefficient	Std.Err.
Planning	-0.178*	(0.0955)	-0.118	(0.100)
Exercise	-0.341***	(0.0937)	-0.302***	(0.0984)
Vegetable	0.0410	(0.0892)	0.0603	(0.0921)
Fruit	-0.0922	(0.0902)	-0.0797	(0.0939)
Age	0.0172**	(0.00798)	0.0186**	(0.00844)
Female	-0.00353	(0.0900)	-0.0506	(0.108)
COB2	-0.333***	(0.125)	-0.317**	(0.129)
COB3	-0.279	(0.247)	-0.221	(0.251)
COB4	-0.295	(0.246)	-0.262	(0.256)
COB7	-0.162	(0.295)	-0.359	(0.320)
EDN2			0.140	(0.161)
EDN3			0.0412	(0.195)
EDN4			0.181	(0.171)
EDN5			-0.207	(0.192)
Income1			0.449	(0.304)
Income2			0.747***	(0.251)
Income3			0.352*	(0.198)
Income4			0.181	(0.174)
Income5			0.294*	(0.168)
Income6			0.348**	(0.160)
Income7			0.265*	(0.145)
Marital2			-0.000686	(0.133)
Marital3			-0.606*	(0.350)
Marital4			0.435***	(0.161)
Work2			-0.108	(0.119)
Work3			-0.374	(0.299)
Work4			0.207	(0.192)
Work5			0.276	(0.443)
Work6			-0.00729	(0.643)
Work7			-0.657	(0.399)
Constant	-0.835**	(0.390)	-1.290***	(0.460)
Observations	918		918	
Log Pseudolikelihood	-564.4814		-543.05978	
AIC	1150.963		1148.120	
BIC	1204.007		1297.608	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.10: Single Equation Probit Estimates for Lifestyle Variables; Including Planning

	(1) Exercise		(2) Fruit		(3) Vegetable	
	Coefficient	Std.Err.	Coefficient	Std.Err.	Coefficient	Std.Err.
Planning	0.268***	(0.0960)	0.120	(0.0955)	0.222**	(0.0948)
Age	-0.00259	(0.00833)	0.0177**	(0.00821)	0.00870	(0.00811)
Female	0.0852	(0.104)	0.306***	(0.0990)	0.363***	(0.100)
COB2	-0.145	(0.122)	-0.116	(0.119)	-0.129	(0.119)
COB3	-0.369*	(0.221)	-0.00614	(0.232)	-0.0842	(0.226)
COB4	-0.397	(0.259)	0.197	(0.232)	-0.200	(0.242)
COB5	-0.245	(0.430)	1.098**	(0.498)	-0.148	(0.403)
COB6	0.129	(0.386)	0.387	(0.357)	-0.490	(0.401)
COB7	0.249	(0.294)	-0.244	(0.294)	-0.224	(0.297)
EDN2	0.262*	(0.155)	0.199	(0.161)	0.220	(0.160)
EDN3	0.730***	(0.191)	0.244	(0.192)	0.288	(0.190)
EDN4	0.630***	(0.166)	0.291*	(0.171)	0.159	(0.169)
EDN5	0.790***	(0.184)	0.673***	(0.185)	0.412**	(0.182)
Income1	-0.163	(0.304)	0.320	(0.296)	0.0999	(0.284)
Income2	-0.423*	(0.250)	0.416*	(0.243)	-0.0658	(0.244)
Income3	-0.509***	(0.195)	-0.0318	(0.193)	0.111	(0.188)
Income4	-0.249	(0.172)	0.0593	(0.169)	0.0913	(0.167)
Income5	-0.239	(0.164)	0.297*	(0.156)	-0.0654	(0.155)
Income6	-0.127	(0.163)	-0.0873	(0.152)	-0.0914	(0.148)
Income7	-0.224	(0.143)	0.247*	(0.134)	-0.0387	(0.132)
Marital2	0.0799	(0.135)	-0.163	(0.132)	-0.323**	(0.131)
Marital3	0.568	(0.408)	-0.0509	(0.301)	-0.477	(0.335)
Marital4	0.124	(0.168)	0.0294	(0.162)	-0.249	(0.161)
Work2	-0.0208	(0.119)	-0.167	(0.113)	0.183	(0.112)
Work3	0.426	(0.303)	-0.594*	(0.306)	0.394	(0.289)
Work4	0.334*	(0.188)	-0.362*	(0.185)	0.0486	(0.177)
Work5	0.166	(0.391)	-0.0374	(0.372)	0.765*	(0.397)
Work6	0.310	(0.768)				
Work7	0.761*	(0.425)	-1.060***	(0.395)	-0.236	(0.362)
Constant	0.104	(0.444)	-1.601***	(0.446)	-1.090**	(0.439)
Observations	943		939		939	
Log Psuedolikelihood	-545.256		-603.063		-616.197	
AIC	1150.511		1264.126		1290.394	
BIC	1295.983		1404.626		1430.894	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

consumption. The inclusion of the 'planning' indicator does not make much difference to the estimates of other coefficients, or the average partial effects shown in Table 6.14.

In the single equation probit model there was a negative relationship between planning and obesity, even after controlling for diet and exercise. To test whether there is a separate effect of planning on obesity propensity in the more robust MVP model, the same multivariate probit specification was again estimated, with the only difference being the inclusion of the planning variable in the obesity equation. Those estimates, shown in Table 6.12, do not find a statistically significant coefficient on the planning variable in the obesity equation (coefficient:0.0428, p-value:0.648). So there is little evidence of an independent effect of planning on obesity, once diet and exercise have been appropriately controlled for. This supports the hypothesis that the relationship between planning and obesity occurs through the pathways of diet and exercise.

Table 6.11: MVP System Estimation, Including Planning in Lifestyle Equations

	Obese	(Std.Err.)	Exercise	(Std.Err.)	Fruit	(Std.Err.)	Vegetable	(Std.Err.)
Exercise	-0.653*	(0.346)						
Vegetable	-1.094***	(0.243)						
Fruit	-0.284	(0.356)						
Planning			0.247**	(0.0978)	0.107	(0.0962)	0.181**	(0.0848)
Age	0.0160**	(0.00738)	-0.00263	(0.00856)	0.0173**	(0.00819)	0.00618	(0.00800)
Female	0.185**	(0.0941)	0.0948	(0.104)	0.307***	(0.100)	0.376***	(0.0948)
COB2	-0.334***	(0.114)	-0.142	(0.125)	-0.127	(0.122)	-0.147	(0.118)
COB3	-0.269	(0.219)	-0.347	(0.240)	-0.00431	(0.229)	-0.0718	(0.220)
COB4	-0.322	(0.226)	-0.385	(0.237)	0.193	(0.238)	-0.186	(0.234)
COB5	-2.070	(3.231)	-0.275	(0.419)	1.080**	(0.481)	-0.290	(0.393)
COB6	-4.623	(109.6)	0.157	(0.370)	0.408	(0.348)	-0.431	(0.369)
COB7	-0.196	(0.273)	0.289	(0.327)	-0.227	(0.300)	-0.178	(0.295)
EDN2			0.216	(0.157)	0.154	(0.168)	0.0555	(0.142)
EDN3			0.676***	(0.195)	0.197	(0.196)	0.124	(0.169)
EDN4			0.565***	(0.176)	0.236	(0.176)	-0.0153	(0.148)
EDN5			0.752***	(0.188)	0.637***	(0.187)	0.295*	(0.166)
Income1			-0.219	(0.304)	0.249	(0.298)	-0.0838	(0.252)
Income2			-0.510**	(0.256)	0.313	(0.262)	-0.326	(0.212)
Income3			-0.553***	(0.190)	-0.0764	(0.192)	-0.0164	(0.169)
Income4			-0.278	(0.170)	0.0346	(0.167)	0.0420	(0.142)
Income5			-0.261	(0.161)	0.267*	(0.157)	-0.143	(0.135)
Income6			-0.153	(0.157)	-0.127	(0.150)	-0.164	(0.127)
Income7			-0.240*	(0.140)	0.213	(0.136)	-0.132	(0.117)
Marital2			0.113	(0.133)	-0.124	(0.135)	-0.212	(0.129)
Marital3			0.678*	(0.361)	0.0548	(0.333)	-0.165	(0.295)
Marital4			0.0761	(0.172)	-0.00384	(0.160)	-0.341**	(0.142)
Work2			-0.0200	(0.115)	-0.165	(0.111)	0.178*	(0.0969)
Work3			0.478	(0.332)	-0.608*	(0.312)	0.458*	(0.250)
Work4			0.290	(0.194)	-0.398**	(0.184)	-0.0591	(0.155)
Work5			0.0987	(0.436)	-0.135	(0.420)	0.517	(0.375)
Work6			0.388	(0.651)	-5.737	(949.7)	-5.282	(1,162)
Work7			0.870*	(0.452)	-1.000**	(0.434)	0.00566	(0.333)
Constant	-0.106	(0.403)	0.175	(0.458)	-1.501***	(0.455)	-0.730*	(0.430)
Observations	943		AIC	4837.5441		BIC	5361.2433	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.12: MVP System Estimation, Including Planning in All Equations

	Obese	(Std.Err.)	Exercise	(Std.Err.)	Fruit	(Std.Err.)	Vegetable	(Std.Err.)
Exercise	-0.663*	(0.344)						
Vegetable	-1.110***	(0.230)						
Fruit	-0.319	(0.349)						
Planning	0.0428	(0.0938)	0.254***	(0.0983)	0.112	(0.0960)	0.201**	(0.0937)
Age	0.0155**	(0.00742)	-0.00275	(0.00856)	0.0171**	(0.00820)	0.00575	(0.00805)
Female	0.196**	(0.0954)	0.0961	(0.104)	0.308***	(0.100)	0.377***	(0.0946)
COB2	-0.333***	(0.113)	-0.142	(0.125)	-0.128	(0.122)	-0.148	(0.118)
COB3	-0.267	(0.217)	-0.346	(0.240)	-0.00368	(0.229)	-0.0740	(0.220)
COB4	-0.315	(0.225)	-0.383	(0.237)	0.194	(0.238)	-0.179	(0.233)
COB5	-10.01	(0.000)	-0.276	(0.419)	1.074**	(0.480)	-0.296	(0.389)
COB6	-11.21	(0.000)	0.161	(0.370)	0.413	(0.348)	-0.422	(0.370)
COB7	-0.196	(0.272)	0.291	(0.327)	-0.227	(0.300)	-0.180	(0.295)
EDN2			0.213	(0.158)	0.147	(0.168)	0.0465	(0.141)
EDN3			0.671***	(0.195)	0.189	(0.197)	0.112	(0.168)
EDN4			0.560***	(0.177)	0.227	(0.177)	-0.0260	(0.148)
EDN5			0.747***	(0.189)	0.628***	(0.188)	0.281*	(0.166)
Income1			-0.222	(0.304)	0.240	(0.297)	-0.0894	(0.249)
Income2			-0.512**	(0.255)	0.304	(0.261)	-0.328	(0.209)
Income3			-0.553***	(0.190)	-0.0794	(0.191)	-0.0135	(0.167)
Income4			-0.278	(0.170)	0.0321	(0.166)	0.0426	(0.140)
Income5			-0.261	(0.161)	0.264*	(0.156)	-0.143	(0.134)
Income6			-0.153	(0.157)	-0.129	(0.149)	-0.161	(0.126)
Income7			-0.240*	(0.140)	0.209	(0.136)	-0.133	(0.116)
Marital2			0.115	(0.133)	-0.119	(0.135)	-0.206	(0.128)
Marital3			0.682*	(0.361)	0.0642	(0.331)	-0.159	(0.292)
Marital4			0.0757	(0.172)	-0.00570	(0.159)	-0.340**	(0.141)
Work2			-0.0201	(0.115)	-0.165	(0.111)	0.178*	(0.0959)
Work3			0.481	(0.332)	-0.609**	(0.311)	0.461*	(0.248)
Work4			0.289	(0.194)	-0.400**	(0.183)	-0.0600	(0.154)
Work5			0.0941	(0.436)	-0.145	(0.419)	0.510	(0.373)
Work6			0.395	(0.649)	-7.869	(0)	-7.922	(0)
Work7			0.876*	(0.452)	-0.988**	(0.434)	0.0170	(0.330)
Constant	-0.0824	(0.404)	0.179	(0.458)	-1.487***	(0.455)	-0.715*	(0.429)
Observations	943		AIC	4839.3619		BIC	5367.9101	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6.13: Correlation Coefficient Estimates from MSL Procedure

	Obese	Exercise	Fruit	Vegetable
Planning in Lifestyle Equations				
Obese	1.000			
Exercise	0.297	1.000		
Fruit	0.271	0.137**	1.000	
Vegetables	0.769***	0.053	0.225***	1.000
Planning in All Equations				
Obese	1.000			
Exercise	0.307	1.000		
Fruit	0.296	0.138**	1.000	
Vegetables	0.782***	0.054	0.225***	1.000

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

Table 6.14: Estimates of Average Partial Effect on Obesity Propensity

	Probit (Exclusions) (Planning in X'_O)	Probit (NoExclusions) (Planning in X'_O)	MVP (Exclusions) (Planning in X'_E, X'_F, X'_V)	MVP (Exclusions) (Planning in X'_E, X'_F, X'_V,X'_O)
Exercise	-0.124	-0.105	-0.210	-0.212
	(0.009)	(0.016)	(0.051)	(0.053)
Vegetable	0.014	0.020	-0.353	-0.357
	(0.002)	(0.004)	(0.073)	(0.076)
Fruit	-0.032	-0.027	-0.088	-0.098
	(0.003)	(0.005)	(0.027)	(0.031)

Standard deviations are shown in parentheses.

6.7 Conclusion

The analysis methodologies used in the earlier chapters of this thesis abstracted from the particular pathways of diet and exercise through which other variables influenced body weight outcomes. This chapter used the modern statistical technique of Maximum Simulated Likelihood to simultaneously estimate systems of equations for obesity, diet, and exercise. Through this it was possible to gain a more accurate understanding of the pathways that lead to obesity. The estimated correlation coefficients between the error terms of the equations gave empirical support to the usage of this methodology relative to single equation approaches.

An important result from this analysis was the large difference in estimated average partial effects of the diet and exercise variables on obesity propensity depending on the estimation procedure. By using the MVP system estimation procedure, which allows for unobservables that affect diet, exercise and obesity, the estimated average partial effect of exercise on obesity propensity more than doubled, and large effects became apparent in the expected directions for fruit and vegetable consumption that were not present in the single equation model. These results contribute to the literature regarding the relative importance of diet and exercise in the determination of obesity. The findings provide evidence of the importance of taking a systems approach to the joint estimation of diet, exercise and body weight outcomes.

A variable representing planning behaviour was incorporated in the analysis in an extension. Although the planning variable was significantly associated with several of the lifestyle variables, whether or not the variable was included did not greatly affect the estimates of other coefficients, which is a good sign since it suggests the usual practice of excluding it may not significantly bias results. Evidence was also found that the effect of the planning variable on obesity does as expected operate through the diet and exercise variables, so that there is no significant effect of planning on obesity once these variables have been controlled for in the MVP specification.

Chapter 7

Conclusion

This thesis analysed the determinants of lifestyle choices that are important to body weight outcomes. The main focus was on the importance of intertemporal trade-offs to these choices. The research presented was interdisciplinary in nature, building predominantly on the theory and methodologies from economics, but also incorporating other areas such as psychology, epidemiology, medicine and health research. Measures of intertemporal discounting behaviour were used to test hypotheses regarding the importance of discounting as a risk factor for high body weight outcomes, the potential for smoking status to act as a mitigating factor in these relationships, and the lifestyle choice pathways through which discounting operates.

In Chapter 3, two survey questions were developed to elicit discount rates in the monetary domain and the health domain. These stated preference questions were constructed to be able to discriminate between different discounting behaviour, and to be comparable to one another. Using data from the popultation representative South Australian Health Omnibus Survey 2008 including responses to these questions, it was shown that the elicited discounting variables could not be well explained by other individual characteristics, and thus represent a unique aspect of individual variation. Furthermore, there was found to be little correlation between discounting in the monetary domain and discounting in the health domain.

In Chapter 4 the indicators of intertemporal discounting were used to analyse the relationship between discounting and body weight outcomes. After controlling for other demographic characteristics, intertemporal discounting as measured by an indicator variable for discounting in the monetary domain was found to be positively associated with BMI. This is in contrast to previous studies that have not found this relationship, and reasons for this are discussed in the chapter. Various models were estimated to explain BMI, and the probability of being overweight or obese. Although the exact magnitude of the estimated effect of discounting on body weight did vary depending on the specification used, it was a robust finding across the methodologies that this association was positive and statistically significant. Furthermore, the estimated magnitude of the partial effect was of a similar magnitude to the estimated partial effects of income and education, which are commonly accepted risk factors for obesity. This suggests that individuals' heterogeneous rates of intertemporal discounting are important determinants of body weight that are often not recognised, and should be given more consideration in policy decisions and further resarch.

There are reasons to believe that the effect of various individual characteristics on BMI outcomes may differ depending on the individual's current position on the BMI distribution. Quantile regression was used to allow the partial effect of each explanatory variable on BMI to differ across the conditional quantiles of BMI. The point-estimates of the effect of discounting on BMI tended to increase at higher quantiles, suggesting that the effect could be stronger in the obese range. However there was insufficient statistical evidence to strongly support the hypothesis of an increasing effect.

Throughout the analysis of Chapter 4, indicators of discounting in the monetary and health domain were used. The positive results that were found for the monetary domain indicator were in contrast to the health domain variable, which had an effect that was statistically insignificant in all specifications. This result was in fact similar to some previous studies which found that a monetary domain indicator of discounting was associated with health outcomes, while a health domain indicator was not. It is likely that these findings are simply due to the relatively poorer quality of the health domain variables. While trade-offs over time with money are a common type of decision that individuals would be familiar with, similar trade-offs made for health outcomes are less common, and subjects' unfamiliarity with the type of questions in the health choice scenario they are asked may make the variable less reflective of true preferences. This could also suggest that refinements of the techniques to elicit intertemporal preferences in the health domain may be a useful area of further research. The results that a monetary domain indicator of discounting performs better than a health domain indicator to explain a health outcome is fortuitous, since the monetary domain questions are the 'standard' procedure.

While the main questions of interest in Chapter 5 related to the joint relationships between discounting, smoking and body weight, it was first necessary to investigate the individual relationship between intertemporal discounting and smoking. Evidence was found of a positive association between discounting and smoking using the SAHOS dataset. This result is of particular importance since there are some models of smoking behaviour that are perfectly myopic, and the result here supports a future-oriented model. In particular it was found that discounting was associated both with being a current and a former smoker, relative to being a 'never smoker'. This suggests that discounting is a stable trait that is a determinant of smoking behaviour, rather than a result of current smoking behaviour as suggested by some researchers. Sequential estimation also provided evidence that discounting is a predictor of smoking commencement, rather than smoking cessation. This result may have practical application in terms of the targetting of anti-smoking interventions towards certain types of individuals.

Evidence was presented that the effect of discounting on body weight occurs primarily for non-smokers, rather than for smokers. A higher rate of discounting is associated with increased smoking, and thus within the subsample of smokers while there is still a positive direct effect of discounting on body weight, this is mitigated by the effect of smoking quantity on body weight. Allowing the effect of discounting on body weight to differ by smoking status raised the estimated effect of discounting on BMI by almost 30% for non-smokers. Evidence was also shown that controlling for discounting may be important for estimates of the effect of smoking on body weight.

Chapter 6 took a different approach to the estimation of models of body weight outcomes by analysing the role of diet and exercise in obesity determination using simultaneous equation estimation that allowed for the presence of unobserved variables that affect obesity, diet and exercise. The dataset used in this chapter was the North West Adelaide Health Study, and the sample was restricted to baby boomers. Maximum Simulated Likelihood techniques were used to estimate Multivariate Probit systems of equations for obesity, diet, and exercise. Correlation coefficients that were estimated within the MSL procedure provided evidence that this approach was more suitable than single equation approaches.

A naive single equation approach did not find a significant effect of diet on obesity propensity, and estimated an average partial effect of being an exerciser on the probability of obesity of only -13.1%. However, using the MVP system approach the diet variables became statistically significant, and average partial effects were estimated for all diet and exercise variables that were much larger reductions in the probability of obesity. These estimated effects seem more likely given the known relationships between diet, exercise and obesity, and thus these results show the benefit of using the MVP system approach over the naive single equation approach. A variable representing planning behaviour was incorporated into the MVP system estimation. This variable represents a different aspect of intertemporal choice behaviour to the previously used measures of intertemporal discounting. It was found that the inclusion or exclusion of this variable did not greatly alter the estimated results. Evidence was also presented that the effect of planning on obesity propensity is due to its effect on the exercise and diet variables.

This thesis contributes to and complements the existing literature regarding the important role of intertemporal choice behaviour as a determinant of body weight. The findings of this thesis contribute to the understanding of the decisions that lead to various body weight outcomes. By doing so, they can provide useful insights into questions regarding whether public policy should intervene in these decisions, and how interventions should be constructed to align with individuals' incentives.

The importance of discounting can for example be used as a rationale for interventions based on the usage of immediate costs and benefits to promote healthier behaviours. An example of this is the experiment of Volpp et al. (2008), where it was found that use of daily financial incentives was beneficial for weight loss behaviour in the short term. There is clearly much more research to be done in this emerging area, including improvement in the tools used to measure relevant discounting behaviour, and Randomized Controlled Trials of interventions based on this theory. There are also many policy implications from the joint analysis of smoking behaviour, the results of which suggested that the stated-preference indicator of intertemporal discounting could be used as a screening tool for those at risk of smoking commencement, or those at risk of weight gain upon smoking cessation. Such particular policy suggestions are beyond the direct scope of this thesis, but are certainly promising areas for further research based on the robust basis of the analysis in this thesis.

Appendix A

Chapter 3 Analysis: Unrestricted Sample

Introduction

This appendix reproduces the analysis from Section 3.5 where appropriate on the full sample of 2824 observations, that has not been restricted in line with the sample used in Chapter 4 and Chapter 5. The information presented here shows that the data exclusions used in Section 3.5 did not have a large impact on the results, as similar results are found using the larger sample.

Descriptive Statistics

This sample is comprised of 56.41% females, and 43.59% males. The average age is 49.2, with a range from 15 to 96 years of age.

Tables A.1 and A.2 summarize the responses to monetary domain and health domain intertemporal choice questions respectively.

Table A.1: Summary of Responses to Question One (Monetary Domain)

Response	Implied Range of ρ	Frequency	Percent
Prefer to pay the fine now	$-1 < \rho \leq 0$	2245	81.49
\$200	$0 \leq \rho \leq 0.05$	315	11.43
\$220	$0.05 \leq \rho \leq 0.15$	84	3.05
\$240	$0.15 \leq \rho \leq 0.25$	51	1.85
\$260	$0.25 \leq \rho \leq 0.35$	12	0.44
\$280	$0.35 \leq \rho \leq 0.45$	5	0.18
\$300	$0.45 \leq \rho \leq 0.5$	15	0.54
Prefer later still	$\rho \geq 0.5$	28	1.02
Missing Value	N/A	69	N/A

The proportion of respondents who show evidence of a positive discount rate in the monetary domain is 18.51%, and the proportion who show ev-

Table A.2: Summary of Responses to Question Two (Health Domain)

Response	Implied Range of ρ_H	Frequency	Percent
Prefer now	$-1 < \rho_H \leq 0$	2367	89.73
10 days	$0 \leq \rho_H \leq 0.05$	191	7.24
11 days	$0.05 \leq \rho_H \leq 0.15$	7	0.27
12 days	$0.15 \leq \rho_H \leq 0.25$	9	0.34
13 days	$0.25 \leq \rho_H \leq 0.35$	2	0.08
14 days	$0.35 \leq \rho_H \leq 0.45$	1	0.04
15 days	$0.45 \leq \rho_H \leq 0.5$	17	0.64
Prefer even longer extension	$\rho_H \geq 0.5$	44	1.67
Missing Value	N/A	186	N/A

idence of a positive discount rate in the health domain is 10.27%. These figures are quite similar to those for the restricted sample used in Section 3.5, 19.06% and 10.33% respectively.

Domain Independence

Tables A.3 and A.4 show the contingency tables for the binary indicators and discounting responses respectively. The correlation coefficient between the binary variables is 0.085, and for the raw responses is 0.010 (Pearson) or 0.076 (Spearman). Pearson's Chi-squared test rejects the null hypothesis of independence with a p-value of 0.000 in both cases.

Table A.3: Contingency Table for Binary Discounting Indicators

		Health Discounter (PDR-H)			
		No	Yes	Refused	Total
Monetary Discounter (PDR-M)	No	1933	190	122	2245
	Yes	413	76	21	510
	Refused	21	5	43	69
	Total	2367	271	186	2824

Table A.4: Contingency Table for Discounting Responses

		ρ_H									
		A	Bi	Bii	Biii	Biv	Bv	Bvi	C	Refused	Total
ρ	$-1 < \rho \leq 0(A)$	1933	127	7	7	2	0	11	36	122	2245
	$0 \leq \rho \leq 0.05$ (Bi)	245	47	0	0	0	1	4	5	13	315
	$0.05 \leq \rho \leq 0.15$ (Bii)	68	7	0	1	0	0	2	2	4	84
	$0.15 \leq \rho \leq 0.25$ (Biii)	47	2	0	0	0	0	0	0	2	51
	$0.25 \leq \rho \leq 0.35$ (Biv)	12	0	0	0	0	0	0	0	0	12
	$0.35 \leq \rho \leq 0.45$ (Bv)	4	0	0	1	0	0	0	0	0	5
	$0.45 \leq \rho \leq 0.5$ (Bvi)	14	0	0	0	0	0	0	1	0	15
	$\rho \geq 0.5$ (C)	23	3	0	0	0	0	0	0	2	28
	Refused	21	5	0	0	0	0	0	0	43	69
	Total	2367	191	7	9	2	1	17	44	186	2824

Appendix B

NWAHS Data Description

Table B.1: Variable Descriptions

Variable Name	Description
Obese	A binary variable taking the value 1 if the respondent has a Body Mass Index greater than 30
Exercise	A binary variable taking the value 1 if the respondent undertakes some exercise, and taking the value 0 if the respondent is sedentary
Fruit	A binary variable taking the value 1 if the respondent states that they usually eat at least 2 serves of fruit per day
Vegetable	A binary variable taking the value 1 if the repondent states that they usually eat at least 3 serves of vegetables per day
Planning	A binary variable to indicate whether the respondent has undertaken some planning for retirement
Age	The respondent's current age at Stage 2 of the NWAHS
Female	A binary variable indicating the respondent's sex. Takes the value 1 if respondent is female.
Country of Birth	A series of dummy variables indicating country of birth. The baseline category is Australia.
COB2	UK or Ireland
COB3	Southern Europe
COB4	Northern and Western Europe
COB5	Eastern Europe, the former-USSR and the Baltics
COB6	Asia
COB7	Other
Education	A series of dummy variables indicating highest educational achievement. The baseline category is 'left school at 15 years or less'.
EDN2	A binary variable indicating 'left school after age 15' as highest educational achievement.
EDN3	A binary variable indicating 'Trade or Apprenticeship' as highest educational achievement.
EDN4	A binary variable indicating 'Certificate or Diploma' as highest educational achievement.
EDN5	A binary variable indicating 'Bachelor Degree or higher' as highest educational achievement.

Table B.2: Variable Descriptions (continued)

Variable Name	Description
Income	A series of dummy variables indicating approximate annual gross household income. The baseline category is 'more than \$80000'.
Income1	A binary variable indicating approximate annual gross household income is between \$0 and \$12000.
Income2	A binary variable indicating approximate annual gross household income is between \$12001 and \$20000.
Income3	A binary variable indicating approximate annual gross household income is between \$20001 and \$30000.
Income4	A binary variable indicating approximate annual gross household income is between \$30001 and \$40000.
Income5	A binary variable indicating approximate annual gross household income is between \$40001 and \$50000.
Income6	A binary variable indicating approximate annual gross household income is between \$50001 and \$60000.
Income7	A binary variable indicating approximate annual gross household income is between \$60001 and \$80000.
Marital Status	A series of dummy variables indicating relationship status. The baseline category is 'married or living with partner'.
Marital2	A binary variable indicating relationship status as 'separated or divorced'.
Marital3	A binary variable indicating relationship status as 'widowed'.
Marital4	A binary variable indicating relationship status as 'never married'.
Work Status	A series of dummy variables indicating work status. The baseline category is full-time employed.
Work2	A binary variable indicating work status as 'part-time or casual employment'.
Work3	A binary variable indicating work status as 'unemployed'.
Work4	A binary variable indicating work status as 'home duties'.
Work5	A binary variable indicating work status as 'retired'.
Work6	A binary variable indicating work status as 'student'.
Work7	A binary variable indicating work status as 'other'.

Table B.3: Summary Statistics

Variable	**Mean**	**Std. Dev.**
Obese	0.318	0.466
Exercise	0.690	0.463
Vegetable	0.434	0.496
Fruit	0.416	0.493
Planning	0.667	0.472
Age	48.052	5.562
Female	0.548	0.498
COB1	0.723	0.448
COB2	0.158	0.365
COB3	0.036	0.187
COB4	0.034	0.181
COB5	0.012	0.107
COB6	0.015	0.121
COB7	0.022	0.148
EDN1	0.097	0.295
EDN2	0.335	0.472
EDN3	0.139	0.346
EDN4	0.245	0.43
EDN5	0.185	0.388
Income1	0.043	0.204
Income2	0.054	0.226
Income3	0.09	0.287
Income4	0.119	0.324
Income5	0.137	0.344
Income6	0.14	0.347
Income7	0.2	0.401
Income8	0.216	0.412
Marital1	0.718	0.45
Marital2	0.173	0.378
Marital3	0.019	0.137
Marital4	0.09	0.287
Work1	0.61	0.488
Work2	0.253	0.435
Work3	0.025	0.158
Work4	0.077	0.267
Work5	0.013	0.112
Work6	0.004	0.065
Work7	0.017	0.129
N	943	

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