The Influence of Time Preferences on the Development of Obesity: Evidence from a General Population Longitudinal Survey

Ewan Gray

Health Economics Research Unit (HERU), University of Aberdeen

Short Abstract

In the economics of health behaviours literature individual's preferences are hypothesised to be important determinants of obesity. Time preferences describe how people value the timing of costs and benefits and have particular relevance for obesity. This is because perceived costs of obesity (loss of health and longevity) occur far in the future while perceived benefits of calorie-imbalance (utility of food consumption and alternative uses of time instead of physical activities) are immediate.

Aims

This study aims to improve knowledge of the potential effect of time preferences on the development of obesity by exploiting an existing longitudinal data set.

Methods

The DHS is a household survey comprising of 2000 households representative of the Netherlands population. Seventeen years of data are available for analysis. The Consideration of Future Consequences Scale (CFCS) is used as the measure of time preferences. Four different econometric models are used to explore the effect of time preferences on the development of obesity.

Conclusions

Results support a small but statistically significant effect of time preferences on risk of developing obesity. The high prevalence of obesity means this small effect has some public health importance.

Acknowledgements

The Chief Scientist Office of the Scottish Government Health Directorates funds HERU. The views expressed in this paper are those of the authors only and not those of the funding body. EG receives financial support through a PhD studentship from the Institute of Applied Health Sciences, University of Aberdeen and the Medical Research Council.

Many thanks to all the HERU staff for useful comments on previous drafts.

Introduction

Obesity is one of the greatest public health issues in many societies today. What causes some individuals to become obese while others do not? What has caused the dramatic rise in the prevalence of obesity? These questions are the subject of much research and theory.

One factor that has been suggested in response to both questions is individual's preferences. Time preferences, the preferences governing the subjective weighting of costs and benefits occurring at more or less distant points in time, have particular relevance to obesity. It is hypothesised that present-orientated time preferences are associated with a greater likelihood of becoming obese. This is because present-orientated individuals will place very low values on long-term future health benefits when making decisions that determine their future BMI such as dietary or physical activity choices.

Previous studies, reviewed below (table 1), show an association of more present-orientated time preferences with greater BMI. This study furthers this line of research by making use of a longitudinal data set to provide a stronger test of the time preference and obesity association.

Theoretical Basis

Two converging roots can be found in the theoretical literature for the time preference and health (including obesity) relation. These can be labelled the economics root and the psychology root.

The economics root makes particular reference to Grossman (1972) and the health capital model. This model proposes that individuals have health stocks that are depleted as they age. Investments may be made to increase these stocks or postpone depletion. These may take the form of health care or engaging in health promoting behaviours and not engaging in health damaging ones. The extent of investment depends on costs to the individual measured by the "shadow price" of health (time, money, forgone pleasurable activities). The costs may often occur far earlier than the benefits of health investment and it is for this reason that time preferences play an important role. The extent an individual values future benefits and costs less and present costs more determines the attractiveness of potential health investments.

In the health capital model the product of health capital is a flow of healthy days from a given level of health capital stock. As the level of the stock increases more healthy days are available. However there are diminishing returns to health capital.

$h = h(H), h' > 0, h'' < 0$

H is health capital stock; h is number of healthy days.

The change is heath stock over time is determined by net investment (depreciation plus investment) as:

$$\dot{H} = I - \delta H$$

I is gross investment and δ is the rate of depreciation of health stock.

Health investment in the health capital model is determined by the equilibrium of the supply of health from household production and demand for health. This occurs when the marginal benefit of a unit of health equals the marginal cost of supplying it. Marginal benefit is constructed as a sum of wage and non-wage benefits. The individual seeks to maximize the present value of the sum of wage and non-wage benefits less health investment costs across all future time periods, given by the expression (Dardanoni 1986):

$$max \int_{0}^{\infty} e^{-rt}\{(p + w)h - \pi I\}dt$$

r is the individual's time preference rate, w is the wage benefit and p is the non-wage (psychic) benefit. π is the marginal cost of a health investment.

Incorporating health stock depreciation by replacing investment (I) with net investment (H + δH), continuing to discount all arguments by the time preference rate, the individual's maximization problem is then given by:

$$\max \int_{0}^{\infty} e^{-rt}\{(p + w)h(H) - \pi(H + \delta H)\}dt$$

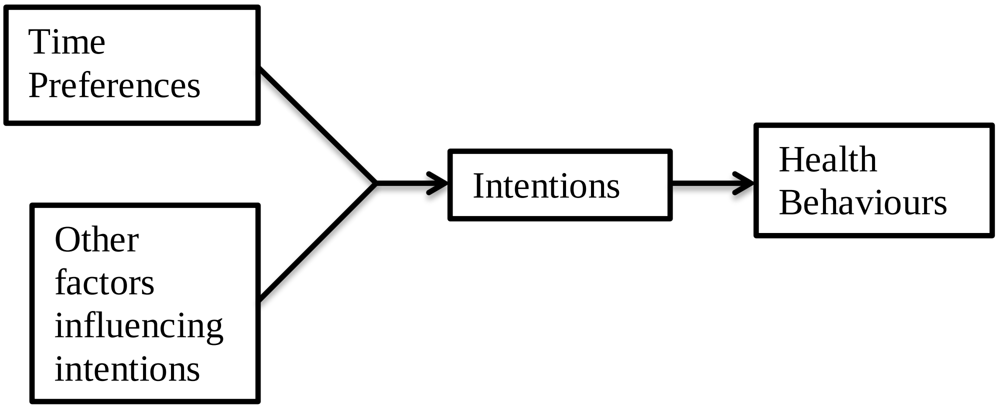
A solution via Euler's equation shows equilibrium can be found at:

$$(p + w)h'(H) = \pi(r + \delta) - \dot{\pi}$$

Therefore when r is greater $h'(H)$ is greater, as $h'' < 0$, this implies that the maximizing level of health stock (H) is smaller when time preference rate is higher. An example of a smaller health stock would be obesity compared to normal BMI.

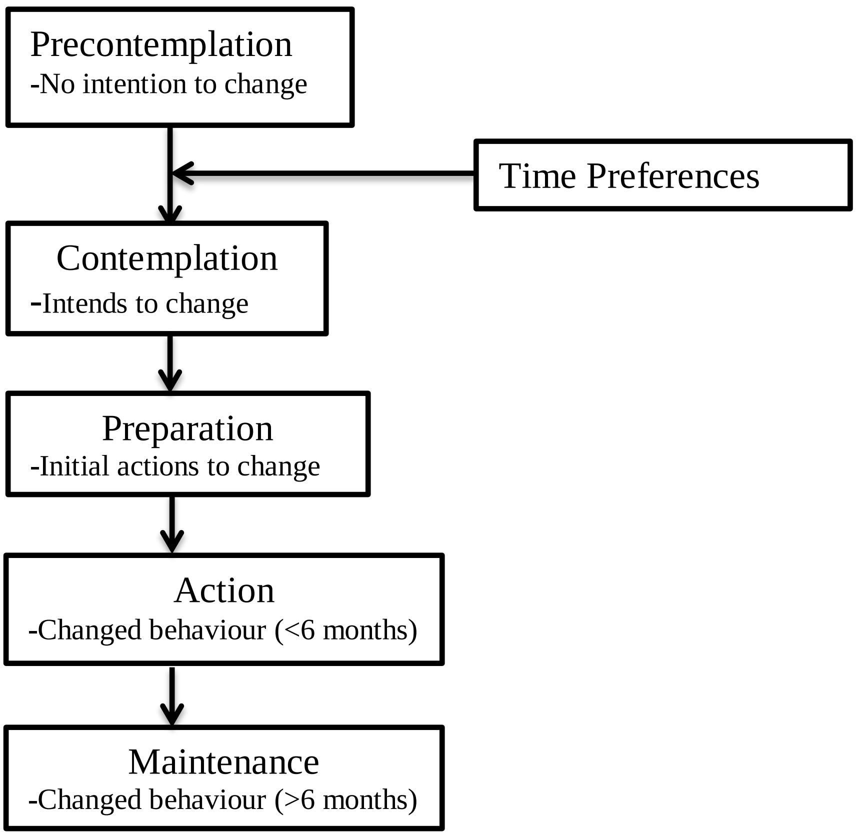
The psychology root is more widely dispersed. A clear time preference and health link was established with the development of the Consideration of Future Consequences scale (CFCS) (used in this study) (Strathman 1994). The issue of long term health effects of health related behaviours is referenced as the key concern in measuring the degree to which an individual considers future compared to present outcomes. The CFCS-health link can be understood in the context of several psychological theories that incorporate a final common pathway from intentions to behaviour (see figure 1) such as the theory of planned behaviour, theory of reasoned action, attitude-behaviour theory and protection-motivation theory among others (Sheeran 2002). In these paradigms an individual's time preferences influence intentions that are the primary determinant of health-related behaviours.

Figure 1 – General Intention Behaviour Model



A popular model in health psychology is the Transtheoretical model (DiClemente and Prochaska, 1982). This is a 5-stage model of behaviour change and maintenance. In the precontemplation stage there is no intention to change behaviour. When an individual moves to the contemplation stage there is intention to change, this may then lead to preparation and eventual action. Time preferences can be viewed as a determinant of movement to the contemplation stage (figure 2).

Figure 2 – Transtheoretical Model



Empirical Findings

The role of time preference as a determinant of health has been sought empirically across a range of major health endpoints, intermediate outcomes and health-related behaviours. As most of these are not analogous to obesity discussion is limited only to those studying the effect of time preferences on obesity and BMI.

Nine previous studies have investigated this relationship; these are summarized in table 1. All are observational in nature and five follow a cross-sectional design. The earliest study (Komolos et al, 2004) is an ecological study using aggregate data from the USA.

Komolos et al compared trends in (lagged) savings rates and consumer debt to obesity trends in the NHANES cohort for the period 1970-2000. These trends generally moved in the same direction with the rate of increase accelerating during the same periods. This offers preliminary evidence in favour of an effect of TP on obesity.

Cross-sectional studies improve the strength of the evidence for an effect of TP by using individual level data. Making further use of the NHANES cohort data Smith et al (2005) construct saving/dissaving dummy variables and use these as time preference proxies in regression analyses with BMI or obesity dependents. Dissaving was found to have a statistically significant but small effect but only in some ethnicity and gender sub-groups.

A greater variety of TP measures and proxies were explored by Borghans and Golsteyn (2006) using data from the 2004 wave of the DHS household panel (Netherlands). Each alternative measure was used as an independent variable in a separate regression with BMI as the dependent. These include: 11-items of the CFCS, savings variables, subjective planning horizon and time preference rate. This study provides further evidence for a small effect for time preference measures. Similar to Smith et al (2004) the effect is not significant consistently across both genders and all alternative measures.

A cross-sectional study in North East England (Adams and White, 2009) used a meditational analysis to assess the hypothesis of time preference, measured by CFCS, mediating the relationship between socio-economic position and BMI or obesity. CFCS was found to have a small but statistically significant effect on BMI. Adams and Nettle (2009) found a significant effect for CFCS on BMI but not for other time preference variables.

Ikeda et al (2010) used time preference rate as the preferred measure in a cross-sectional study with a Japanese population representative sample. A larger sample size allows this study to find a small but statistically significant association between time preference and BMI in the expected direction. A significant effect on a binary dependent (BMI>25) is found while the effect on a binary dependant (BMI>30) is non-significant. This could be due to the differences in BMI distribution in Japanese compared to European and North American populations.

Overall the evidence from these studies suggests a small but statistically significant association of present-orientated time preferences with greater BMI. Evidence for an effect on obesity (BMI>30) is lacking. Some studies only found significant effects within sub-samples suggesting previous studies may have been underpowered to detect a small real effect of time preference on development of obesity.

Aims

This study aims to improve knowledge of the potential effect of time preferences on the development of obesity by exploiting an existing longitudinal data set. In addition to improving statistical power from previous studies this will allow analyses that reduce the reverse causality and omitted variable biases that are concerns in cross-sectional studies.

Data

This study uses the full DHS dataset. The DHS (DnB) is a household panel survey conducted in the Netherlands. Currently 16 waves of data from 1993-2009 are available. The original sample comprised 2000 households representative of the Netherlands populations. Households are replaced when drop-outs occur however by 2009 there appear to be only 1660 households. The survey is self-completed online with arrangements made for those without a computer.

The measure of time preferences available in this data is the Consideration of Future Consequences Scale (CFCS). This is an 11-item scale in which each item is a statement relating to how present or future orientated a person is. Respondents are asked to what extent they themselves conform to each statement on a scale of 1 to 7. This gives an overall score of 11 to 77 where 77 is the most present-orientated (corresponds to high TPR) and 11 is the most future orientated (low TPR). Examples of the statements are:

“I am only concerned about the present, because I trust that things will work themselves out in the future.”

“With everything I do, I am only concerned about the immediate consequences (say a period of a couple of days or weeks).”

Table 1 – Selected Previous Studies

Study (Author, date)	Time Preference Measure	BMI Dependent	Categorical or Binary Dependent	Study Sample	Result BMI	Result Categorical
Ikeda et al, 2010	TP rate	Yes	Yes 1.BMI>25 (1,0) 2.BMI>30 (1,0)	2870, Japan 2004	0.273**	1.BMI>25 0.037** 2.BMI>30 -0.003
Adams and White, 2009	CFCS	Yes	No	804, North East England	0.67**	
Adams and Nettle, 2009	CFCS ZTPI TP rate (hyperbolic)	Yes (logBMI)	No	423, USA	CFCS: 1.00** ZTPI: 0.43 TP rate: 0.44	
Borghans and Golsteyn, 2006	TP rate 11 items of the CFCS	Yes	No	2052, Netherlands 2004	TP rate: M:0.123* F:0.066 CFCS: 2 out of 11 items significant at .05 level for men only	
Smith et al, 2005	1."Dissaving" 2."No Saving" dummy variables	Yes	Yes BMI>30 (1,0)	Approx. 30 million, USA	1.M:0.594** F:0.461 2.M:0.529** F:0.533**	1.M:0.282** F:0.214 2.M:0.210 F:0.283**

*** =P<0.01, **=P<0.05, *=P<0.1,M=male and F=female
ZTPI = Zimbardo Time Perspective Inventory

Note on Selection of Studies:
Four studies rejected on for reasons of study design and quality (Komlos et al, Weller et al, Rasmussen et al, Zhang and Rashad). Komlos et al used group level data while Weller et al followed a case-control design, these were excluded based on study design incomparability. Non-comparable TP measures were issues for Zhang and Rashad (willpower as proxy for TP), Weller et al (AUC) and Rasmussen et al ("bites of food" discount rate). Further Rasmussen et al and Weller et al used samples of students only. Rasmussen et al used percentage body fat rather than BMI as the outcome measure.

Methods

Four alternative statistical approaches are taken by this study; panel data regression (PDR) analysis using a continuous BMI dependent, PDR using an obesity binary response dependent, PDR using an obesity binary response dependent conditional on a lagged dependent and duration analysis (also called survival analysis). All approaches seek to determine the effect of time preference on obesity controlling for socio-demographic variables.

Using an obesity binary response variable, equal to 1 if BMI is greater than 30 and 0 otherwise, is justified by the fact that it is unhealthy BMI in general and obesity in particular that is of interest to health researchers rather than the causes of differences in BMI levels within the 'healthy' range (18-25). This is particularly important if the effect of time preference on BMI is non-linear or heterogeneous. There are theoretical and empirical (Ikeda et al 2010) reasons to believe present-orientated preferences would be associated with lower BMI for some groups, for example those at risk of being underweight (BMI<18).

Panel data regression and duration analysis methods both use the data from all waves of the survey improving statistical power while providing consistent parameter estimates and standard errors. The motivation for using different econometric models is to make further use of the panel structure of the data beyond improving statistical power. Conditioning on a lagged dependent variable gives an indication of the role of state-dependence and will also to some extent control for reverse causality (greater BMI leading to more present-oriented time preferences). Duration analysis performs this same function but with some differences. Models specified with the lagged dependent can be interpreted as a first-order Markov process, i.e. the probability of a state transition is being estimated assuming no influence of history of previous state transitions. Duration models have two differences. Firstly previous state history may have some influence, for example ceteris paribus hazard may increase for every period before occurrence of obesity. Secondly obesity is considered to be an absorbing state meaning individuals are removed from the analysis after the first observation of obesity and provide no further information.

CFCS was chosen as the best available measure of time preference in the data-set. CFCS was measured in every wave while time preference rate was only measure once in 2004. CFCS has previously been shown to be highly correlated with time preference rate and alternative proxies (Borghans and Golsteyn 2006, Adams and Nettle 2009). The one period lag of CFCS is used due to concern of reverse causality and because the lagged value is more likely to reflect time preference in the period relevant for year-to-year weight gain.

Using the full CFCS makes an important assumption that all unit increments on this scale are equal both in relation to where in the range of CFCS scores these occur and which individual items they originate from. This assumption is made on the basis that the CFCS is a validated measure of time perspective/time preference, its development considered issues of redundant elements and scaling. This could be further explored in a sensitivity analysis.

Econometric Models

Panel Data Models

Continuous BMI Dependent

Obesity is most commonly defined by BMI (>30). Therefore an obvious choice of dependent variable is BMI. This is the most efficient way to use the BMI data from this data set. This has been the outcome measure of choice in previous studies. BMI models are included in this study primarily for comparison with previous studies.

BMI is modelled as a linear function of the explanatory variables following the general model (1.1).

$$y_{it} = x_{it}\beta + u_{it} \tag{1.1}$$

x_{it} is the vector of explanatory variables and u_{it} is the error term.

The explanatory variables in the model are CFCS, age, gender and education. Education is coded as two dummy variables summarizing highest educational attainment, one for university education and one for pre-university or senior vocational education (the reference group is less than pre-university or senior vocational education). Income is included in some models as log of the net income composite measure complied by the DHS (not reported). Alternative specifications for the control variables (such as quadratic for age) and interaction terms are explored.

This model can be estimated by OLS. Errors are likely to be correlated across waves by individual therefore in a pooled model the standard errors will be inaccurate. These are replaced by sandwich estimates.

A key concern with such models is omitted variable bias (OVB). Panel data give the opportunity to reduce such bias. Time-invariant individual effects are explicitly included in fixed or random effects models. This controls for unobserved individual heterogeneity, at least for time-invariant variables. These require variation over time of the variables of interest, for the fixed effects this is an absolute requirement, and therefore may not appropriate in the context of time preferences because there is little variation over time of time preferences for most individuals. These models are specified as:

$$y_{it} = x_{it}\beta + \alpha_i + \varepsilon_{it} \tag{1.2}$$

α_i is the time-invariant individual effect and ε_{it} is a time-varying random error term that is independent over waves.

Fixed effect estimators use only the within individual variation in the dependent and explanatory variables. These can be estimated by including individual specific dummy variables in an OLS regression. Random effects models assume the individual effect is uncorrelated with the explanatory variables, $Cov(\alpha_i, x_{it}) = 0$. Radom effects are estimated by generalized least squares (GLS), using the covariance structure specified by the above assumption, resulting in estimates that are a matrix-weighted average of the fixed and between effects.

Probit Models for Panel Data

These data are appropriate for analysis using binary response models. Models such as these focus on the outcome of obesity rather than BMI. Probit models are a class of index model for binary responses, using the probit link function. The dependent variable is binary, coding obese as 1 and non-obese as 0. There are repeated observations (max = 16) on 7413 individuals.

The model specifications of Jones et al (2007), adapted from general health to obesity and the context of these data, are followed by this study. Control variables are the same as those used in the duration model.

Pooled probit models use the data as if it were a cross-section, within and between individual variation are exploited equivalently. This assumes that observations are independent across waves. This is unlikely to be correct because errors are likely to be correlated across waves for the same individual. However, the coefficients from a pooled model are consistent despite this misspecification (Jones et al 2007). The standard errors are replaced by sandwich estimates that are robust to within-individual clustering.

The latent variable specification of the pooled probit:
There are t repeated observations on each individual i. When the continuous latent variable y^*_{it} is greater than zero the binary dependent y_{it} equals 1.

$$
\begin{aligned}
y_{it} &= 1 \leftrightarrow y^*_{it} > 0 \\
y^*_{it} &= x_{it}\beta + u_{it} \qquad (2.1)
\end{aligned}
$$

y^*_{it} is a function of the explanatory variables x_{it} and error term u_{it}. For the probit model u_{it} are independent over t and normally distributed.
The marginal probability of being obese at wave t is then:

$$P(y_{it} = 1/x_{it}) = \Phi[(x_{it}\beta)]$$

Utilising the panel structure of the data, a random effects probit model is specified, parameterizing the individual effect to control for unobserved individual heterogeneity, using the same terms as (1.2):

$$y^*_{it} = x_{it}\beta + \alpha_i + \varepsilon_{it} \qquad (2.2)$$

Models (1.1) and (1.2) predict the probability a randomly selected individual from a randomly selected wave will be obese.

Dynamic Probit Models

Focussing on the observed movements into and out of the obese category rather than simple observation of obesity models can reduce reverse causality bias and provide a stronger causal test of the hypothesis. To explain the causes of individuals becoming obese a state transition probability interpretation is required. Models that capture state dependence by including the lagged dependent variable among the explanatory variables can achieve this. Models specified with a lagged dependent can be interpreted equivalently to a first-order Markov process, i.e. the probability of a state transition is being estimated assuming no influence of history of previous state transitions. The first dynamic model:

$$y*_{it} = x_{it}\beta + \gamma y_{it-1} + \alpha_i + \varepsilon_{it} \quad (3.1)$$

y_{it-1} is the obesity state in the previous time period while γ is the parameter estimated for this regressor. α_i and ε_{it} are defined as in model (1.2).

By including the lagged dependent among the exogenous variables we assume the initial observation of the dependent to be exogenous (Heckman 1981). In fact, this would not be expected to be the case. We would expect the initial observation to be affected by the explanatory variables in the model. One method to account for this suggested by Chamberlain (1982) is to include all leads and lags of explanatory variables in the model in addition to the initial observation. An alternative approach from Jones et al (2007) is to include the within individual means of explanatory variables (an approach developed by Mundlak (1978) to deal with correlated effects) and the first period dependant in addition to a one-period lagged dependant. The unobserved heterogeneity is assumed to be uncorrelated with the explanatory variables conditional on the time averages of these variables. The individual effect is then parameterized as:

$$\alpha_1 = \alpha_0 + \alpha_1 y_{i1} + \alpha_2 \bar{x}_i + u_i$$

y_{i1} is the initial observation of the dependent variable and $\overline{x_i}$ is the mean for explanatory variable x over all waves in the sample for individual i. u_i is assumed to be normally distributed and independent of the explanatory variables, initial conditions and ε_{it}.

Using the random effects specification the model is then,

$$y*_{it} = x_{it}\beta + \gamma y_{it-1} + \alpha_0 + \alpha_1 y_{i1} + \alpha_2 \bar{x}_i + u_i + \varepsilon_{it} \quad (3.2)$$

Duration Analysis

Non-parametric methods allow a broad overview of the data and highlight survival differences between groups. A Kaplan-Meier survival plot allows visualisation of differences in survival by CFCS score quartile. Non-equality of the survival functions of the CFCS quartiles is tested by the log-rank test.

Semi-parametric Cox regression estimates the effect of CFCS controlling for observed covariates. Cox regression is semi-parametric because it does not specify a distribution of survival times (equivalent to not specifying the underlying hazard function).

Hazard is the instantaneous probability of event occurring at time t conditional on survival to time t. The Cox regression model for the hazard of obesity used in this analysis:

$$h(t \mid x) = h(t)\exp(\beta_1 x_1 + \beta_2 x_2 + ... + \beta_N x_N) \qquad (4.1)$$

$h(t)$ is the base-line hazard function. x_1, x_N are the exogenous variables and β_1, β_N are the parameters to be estimated.

This model allows the explanatory variables to influence hazard only through a constant multiplicative effect on the base-line hazard function (the proportional hazards assumption). The (exponentiated) coefficients are interpreted as hazard ratios.

The explanatory variables in these models are CFCS, age, gender, education dummies and initial BMI level. Starting closer to BMI of 30 means BMI>30 will occur more rapidly. Controlling for initial BMI means the estimates for other explanatory variables relate only to their effects on BMI over the observation period.

Results

Summary of Sample

The summary table (2) presents means and proportions for the main variables of interest across each wave. This includes only observations with valid CFCS and BMI values because these are the observations that will be included in the analysis. More observations are usable if either CFCS or BMI is treated as non-time-varying or values are imputed across waves. In this analysis CFCS values are filled forward, i.e. missing values of CFCS are replaced by the CFCS value from the previous wave when possible. This is done largely because CFCS was not measured in 2008 and CFCS variation within individual across waves is low. Education variables are only recorded from 2002. In the following analysis education is not treated as time varying and the highest recorded educational attainment is assigned by individual to observations in all waves.

Table 2 – Summary Statistics

	Mean or % (s.d.)						
Year	**BMI**	**Age**	**CFCS**	**Female**	**University**	**Secondary**	**Obs**
1996	24.4 (3.5)	47 (14.2)	41.63 (11.1)	45.3%	n/a	n/a	3255
1997	24.8 (3.8)	48.1 (14.5)	42.7 (10.6)	45.4%	n/a	n/a	2527
1998	24.8 (3.7)	49.5 (15.1)	43.2 (10.5)	43.4%	n/a	n/a	1293
1999	25.2 (3.8)	50.1 (14.7)	43.8 (10.9)	41.4%	n/a	n/a	1307
2000	24.8 (3.4)	47.2 (15)	43.2 (7.4)	43.3%	n/a	n/a	1030
2001	25.4 (3.8)	47.5 (13.9)	43.9 (8.8)	44.5%	n/a	n/a	1538
2002	25.4 (3.8)	47.4 (14.4)	43.6 (8.3)	44.7%	2%	7.9%	1328
2003	25.6 (4)	49.1 (14.4)	43.5 (8.9)	44%	3.9%	14%	1328
2004	25.7 (4)	50.3 (14.1)	42.2 (8.1)	45.8%	4.8%	17.9%	1714
2005	25.7 (4.2)	49.6 (15.4)	42.4 (8.3)	48.3%	6%	23%	1787
2006	25.8 (4.1)	51.1 (15.4)	42.6 (8.2)	46.8%	5.6%	22.9%	1657
2007	25.8 (4.1)	51.5 (15.2)	42.6 (8)	46.1%	6.8%	25.7%	1688
2008	25.9 (4)	52.5 (15)	n/a	45.9%	7.5%	27.7%	1762
2009	26 (4)	54.9 (14.4)	42.9 (8.2)	44.4%	8.9%	26.9%	1511

Between 1996 and 2009 age, BMI, CFCS increased. Educational attainment also increased although this could be largely due to improving recording of education variables. Increased educational attainment could reflect higher educational attainment in young entrants of later waves. Age and BMI would be expected to increase in an adult sample followed over time. In addition, recent time trends for Western European populations show increasing age and BMI. A greater and increasing in the proportion of men is opposite to what would be expected due to mortality differences.

Continuous BMI Linear Models

Table 3 – BMI Models

Variable	1 – Pooled OLS	2 – Fixed Effects	3 – Random Effects
CFCS (lagged 1 period in 2 & 3)	0.022***(0.004)	0.004*(0.002)	0.005***(0.002)
Age	0.25***(0.019)	0.212***(0.02)	0.19***(0.014)
Gender (Male)	0.221*(0.113)		-0.994***(0.29)
University	-0.427*(0.248)		-0.406(0.31)
U. Secondary	0.788***(0.178)		0.892***(0.163)
Age^2	-0.002***(0.0002)	-0.001***(0.0001)	-0.001***(0.0001)
Gender*Age			0.025***(0.006)
N (Obs)	7413(21515)	5217(15901)	5217(15901)
R^2	0.041	0.017	0.025
rho			0.9

Coef.(s.e.) *=P<0.1 **=P<0.05 ***=P<0.01

The effect of CFCS on BMI is in the expected direction in all models. More present orientated preferences are associated with greater BMI. This is highly statistically significant in the pooled model and random effects (p<0.001) but is only significant at the p<0.1 level for the fixed effects.

Probit Models

Results from models 1 to 4 are presented in table 3

Table 4 – Probit Models

Variable	Model 1 – Pooled Probit	2 – Random effects Probit	3 – R.e. with state dependence	4- R.e. with first period dependent and TV means
CFCS	0.008***(0.002)	0.014***(0.004)	0.011***(0.003)	0.012** (0.005)
Age	0.0567***(0.013)	0.119***(0.027)	0.097***(0.018)	0.163***(0.052)
Gender (Male)	-0.673***(0.203)	-2.33***(0.476)	-1.19***(0.296)	-1.59***(0.408)
University	-0.273*(0.155)	-0.384(0.412)	-0.352(0.271)	-0.56(0.375)
U. Secondary	0.146*(0.077)	0.537***(0.179)	0.246**(0.118)	0.168(0.162)
Age^2	-0.0006*** (0.0001)	-0.0003*** (0.0002)	-0.001*** (0.0002)	-0.001**(0.0005)
Gender*Age	0.008**(0.004)	0.035***(0.009)	0.016***(0.006)	0.046***(0.018)
Obese at t-1			1.7***(0.058)	1.15***(0.069)
Obese at t =1				2.28***(0.138)
<u>Means</u>				
MCFCS				0.008(0.008)
Mage				-0.018(0.058)
$Mage^2$				-0.0003(0.0005)
Mage*Gender				-0.023(0.018)
N(obs)	5183(15737)	5183(15737)	5183(15737)	6199 (18737)
rho		0.955(0.002)	0.687 (0.022)	0.780(0.015)

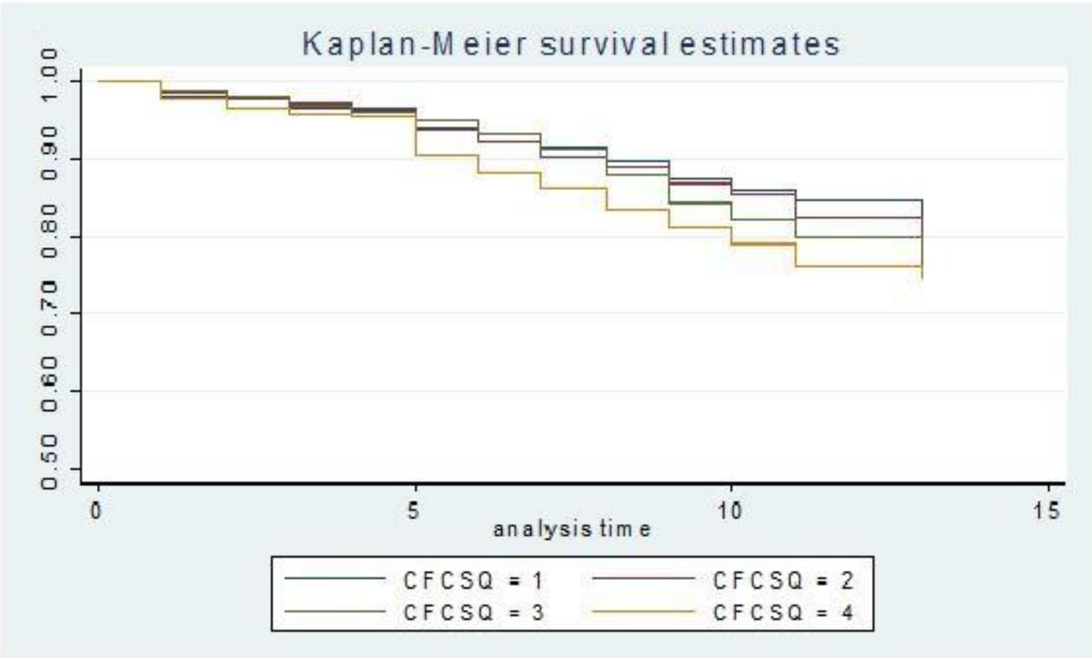
In all models CFCS has a small but statistically significant effect on obesity. The effects of the control variables are similar across the models with some variation among the education variables.

Using the predicted probabilities form model 1, with other covariates fixed at their sample means, an increase of CFCS from mean to one standard deviation above mean shows a relative risk of 1.133. A one standard deviation greater than average CFCS score on average predicts a 13% increased risk of obesity. This is problematic for models 2,3 and 4 because of the presence of strong individual effects (high rho). Assessing the marginal effect of CFCS at the average of the covariates means assessing the probability of a positive outcome when $\alpha_i$is 0 (the mean by assumption), predicted probability of positive outcome at $\alpha_i = 0$ is extremely low. The relative risks are then largely meaningless. For model 2 relative risk is increased by 124%, model 3: 12.8% and for model 4: 34.4%. Odds ratios (95% CIs) for a one standard deviation increase in CFCS, from identically specified logistic regressions (not reported), are: model 1: 1.15 (1.06, 1.25), model 2: 1.25 (1.1, 1.43), model 3: 1.21(1.08, 1.36), model 4: 1.23 (1.03, 1.45).

Duration Analysis

Summary Statistics – Duration Analysis	
19673	Observations
7417	Individuals
62789	Person-years time at risk
916	Failures

Figure 3 - Kaplan-Meier Survival Plot by CFCS Quartile



Log-rank test ($H_0: h_{q1}(t) = h_{q2}(t) = h_{q3}(t) = h_{q4}(t)$), $\chi 2 = 25.19$, $p < 0.0001$

There is a clear difference in the survival functions of the upper CFCS quartiles from the lower CFCS quartiles with the upper quartiles being more likely to become obese over the period. The Log-rank test confirms this difference is statistically significant.

Cox Regression

Variable	Model 1	2 – Quadratic Age	3 - Interactions	4- Initial BMI
CFCS	0.009**(0.004)	0.011***(0.004)	0.011***(0.004)	0.013*** (0.004)
Age	-0.002(0.003)	0.084***(0.018)	0.085***(0.018)	0.052**(0.021)
Gender (Male)	-0.420***(0.075)	-0.413***(0.075)	-0.994***(0.298)	0.224(0.311)
University	-0.266(0.282)	-0.156(0.283)	-0.160(0.283)	0.226(0.284)
U. Secondary	0.462***(0.11)	0.523***(0.111)	0.517***(0.111)	-0.014(0.115)
Age^2		-0.001***(0.0002)	-0.001***(0.0002)	-0.001***(0.0002)
Gender*Age			0.012**(0.006)	-0.006(0.006)
Initial BMI				0.271***(0.006)

Coef.(s.e.) *=P<0.1 **=P<0.05 ***=P<0.01

Model 4 demonstrates that including base-line BMI CFCS still has an effect on the hazard of obesity. The effect of CFCS is not only due to association with base-line BMI, meaning there is an effect on observed weight gains to obesity.

The hazard ratio for standardized CFCS in model 4 is 1.151 (1.07, 1.24). A one standard deviation greater CFCS score is associated with a 15% increased hazard of obesity.

Discussion

Time preferences, as measured by the CFCS scale have a small but statistically significant effect on the development of obesity after controlling for age, gender and education. Due to the high prevalence of obesity this small effect is of some public health importance.

The econometric models using a binary obesity dependent suggest a larger effect for CFCS than those using a continuous BMI dependent. This could be due to the issue of heterogeneous effects.

The fixed effects and random effects models for BMI suggest a smaller effect for CFCS than the pooled model. This may be an underestimate of the true CFCS effect due to little within individual variation in the observation period.

Probit models including a lagged obesity status variable show evidence of strong state dependence as would be expected. CFCS remains statistically significant in these models suggesting that the effect of CFCS is not only due to those that are already obese at first observation having a higher CFCS score.

The results from this study are generally supportive of previous findings for the effect of time preferences on obesity. This study adds to existing knowledge by making use of a larger sample to improve statistical power and by using econometric models for panel data to reduce omitted variable and reverse causality biases. A larger data set could further improve knowledge in this area, especially one with a larger number of waves of data for each individual. A data set with pseudo-random variation of time preferences suitable for methods such as instrumental variables regression could further strengthen causal inference but due to the nature of time preferences this is unlikely to be possible.

Questions remain about the directness of the link between time preferences and obesity. Time preferences could be acting as a proxy for other psychological factors such as risk preferences, self-efficacy or locus of control. This could be further investigated by using a data-set that measures these variables. Intermediate factors in the chain from time preference to obesity would also be of interest. These may include environmental and psychological factors that could be targets for public health policies.

References

Adams, J. & Nettle, D. 2009, "Time perspective, personality and smoking, body mass, and physical activity: An empirical study", *British Journal of Health Psychology,* vol. 14, pp. 83-105.

Adams, J. & White, M. 2009, "Time Perspective in Socioeconomic Inequalities in Smoking and Body Mass Index", *Health Psychology,* vol. 28, no. 1, pp. 83-90.

Borghans, L. & Golsteyn, B. 2006, "Time discounting and the body mass index Evidence from the Netherlands", *Economics and Human Biology,* vol. 4, pp. 39-61.

Chamberlain, G. 1982, "Multivariate Regression Models For Panel Data", *Journal of Econometrics,* vol. 18, no. 1, pp. 5-46.

Dardanoni, V. 1986, "A note on a simple model of health investment", *Bulletin of Economic Research,* vol. 38, no. 1, pp. 97-100.

Grossman, M. 1972, "On the Concept of Health Capital and the Demand for Health", *The Journal of Political Economy,* vol. 80, no. 2, pp. 223-255.

Ikeda, S., Kang, M. & Ohtake, F. 2010, "Hyperbolic discounting, the sign effect, and the body mass index", *Journal of Health Economics,* vol. 29, pp. 268-284.

Jones, A., Rice, N., Bago d'Uva, T. & Balia, S. 2007, *Applied Health Economics,* Routledge.

Komlos, J., Smith, P.K. & Bogin, B. 2004, "Obesity and the rate of time preference: Is there a connection?", *Journal of Biosocial Science,* vol. 36, no. 2, pp. 209-219.

Mundlak, Y. 1978, "On the Pooling of Time Series and Cross Section Data", *Econometrica,* vol. 46, no. 1, pp. 69-85

Prochaska, J. & DiClemente, C. 1982, "Transtheoretical therapy: Toward a more integrative model of change", *Psychotherapy: Theory, Research & Practice,* vol. 19, no. 3, pp. 276-288.

Rasmusssen, E., Lawyer, S. & Reilly, W. 2010, "Percent body fat is related to delay and probability discounting for food in humans", *Behavioural Processes,* vol. 83, pp. 23-30.

Sheeran, P. 2002, "Intention-Behavior Relations: A Conceptual and Empirical Review", *European Review of Social Psychology,* vol. 12, no. 1, pp. 1-36.

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

Strathman, A., Gleicher, F., Boninger, D. & Edwards, S. 1994, "The consideration of future consequences: Weighing immediate and distant outcomes of behavior", *Journal of Personality and Social Psychology,* vol. 66, no. 4, pp. 742-752.

Weller, R., Cook, E., Avsar, K. & Cox, J. 2008, "Obese women show greater delay discounting than healthy-weight women", *Appetite,* vol. 51, pp. 563-569.

Zhang, L. & Rashad, I. 2008, "Obesity and time preference: The health consequences of discounting the future", *Journal of Biosocial Science,* vol. 40, no. 1, pp. 97-113.