A Bivariate Latent Class Correlated Generalized Ordered Probit Model with an Application to Modeling Observed Obesity Levels*

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Abstract

Obesity is a major risk factor for several diseases including diabetes, heart disease and stroke. Increasing rates of obesity internationally are set to cost health systems increasing resources. In the US a conservative estimate puts resources already spent on obesity at $120 billion annually. Given scarce health care resources it is important that categorisation of the overweight and obese is accurate, such that health promotion and public health targeting can be as effective as possible. To test the accuracy of current categorisation within the overweight and obese we extend the discrete data latent class literature by explicitly defining a latent variable for class membership as a function of both observables and unobservables, thereby allowing the equations defining class membership and observed outcomes to be correlated. The procedure is then applied to modeling observed obesity outcomes, based upon an underlying ordered probit equation. We find the standard boundaries for converting

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body mass index into categories may be inappropriate for individuals at the margin, which is then allowed for in estimation.

JEL Classification: C3, D1, I1

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1 Introduction and Background

Obesity is a major risk factor in terms of mortality and morbidity for several major disease groups, including stroke, coronary heart disease, diabetes and certain cancers. Being overweight is second only to tobacco in terms of causes of preventable deaths (Bowlin and Cawley 2007, Liu, Rettenmaier, and Saving 2007). Obesity is defined as a condition of excess body fat. It is hypothesized to be caused by an excess of calories consumed over calories expended, and it can be influenced by numerous causal factors, both genetic and behavioral. One concerning aspect is the increasing rate of obese and overweight individuals, especially in the developed world. In the United States 65% of the population (approximately 195 million individuals) are overweight or obese, and over 30% (over 90 million) are obese. Indeed, not only are these numbers large now, but obesity rates are expected to increase significantly into the foreseeable future (Ruhm 2007).

As a result of the increased numbers of overweight individuals, and the consequent inflated numbers of related diseases, health care costs are increasing. In the US costs related to obesity are already estimated to be at least 6% of health care costs, and these are set to increase (Bowlin and Cawley 2007). As health care constitutes over 16% of GDP in the US (Folland, Goodman, and Stano 2007), this is a significant amount: a conservative estimate puts this figure in excess of $120 billion spent annually on obesity related illness, or over $400 per US citizen ($600 per overweight or obese individual, $1,300 per obese individual per annum).

The most commonly used measure to assess whether an individual is obese or not is the Body Mass Index (BMI), which is the ratio of an individual's weight to the square of height[1]. Individuals with a BMI score of less than 18.5 are classified, based on World Health Organization (WHO) guidelines, as underweight, those with a BMI score of 25 to 30 are classified as overweight and those with a BMI score of greater

[1]We acknowledge BMI may not be the perfect measure for obesity, as it does not distinguish fat from fat free mass (Burkhauser and Cawley 2008). BMI is the measure collected in virtually all social science related datasets, and our proposed method of more flexible boundaries may, in fact, help make classification using BMI somewhat more useful.

than 30 are classified as obese. There may be large differences in health care costs by degree of obesity. For example, overall, a BMI of 35 to 40 has been associated with double the increase in health care expenditure above normal weight. Also, gender differences in how health care is used, and associated costs, change with obesity levels (Andreyeva, Sturm, and Ringel 2004). However, obesity is not just a public health problem, it is an economic phenomenon (see, for example, Philipson 2001, McCarthy 2004). The problem cannot solely be attributed to genetics. The dramatic change in obesity rates have occurred at a rate that cannot be explained by a corresponding change in the gene pool, over such a short period of time. Moreover, obesity is seen as potentially avoidable for certain individuals, behavioral adjustments, for example to diet and physical activity levels, can be made by individuals if perceived benefits exceed costs (Drewnowski 2004).

Given all this, it is important that categorization of those who are overweight and obese be as accurate as possible. This will allow effective targeting of scarce public health and health promotion resources. In this paper we address specific questions concerning observed levels of obesity, as implied by an individual's BMI level and the WHO guidelines. Ultimately we are interested in testing assumptions concerning the relevance of certain individuals' classification within an overweight or obese category, in terms of which groups in society can be most effectively targeted. There is little point targeting certain health promotion campaigns to those who are genetically (or inherently) obese, especially if these individuals' BMI-category levels are unresponsive to lifestyle factors and potential policy tools. Other groups may be inappropriately classified as obese due to strict adherence to the WHO boundaries. For example, athletes and others with high levels of muscle mass and low levels of body fat, might be erroneously classified as being overweight or obese. These ranges might also be inappropriate for older individuals who have lost muscle mass, and consequently have a higher proportion of body fat (NIDDKD 2006).

Our starting point, is to model the observed BMI categories as defined by the WHO, using an ordered probit (OP) approach. However, following a substantial literature in health economics (see, for example, Deb and Trivedi 2002, Bago D'Uva 2005b, Bago D'Uva 2005a) we will also use a latent class approach to account for unobserved heterogeneity across individuals, and implicitly divide individuals into two classes: those inherently obese and those not. We extend the latent class approach by allowing the unobservables driving both class membership and observed BMI-category outcome to be correlated. This is likely *a priori* as these relate to the same individual. Finally, to allow for the fact that the widely accepted WHO boundaries may not be appropriate for certain individuals at the margin, we will allow for the boundary parameters inherent in the OP model to vary by observed individual characteristics.

Our analysis is conducted using 2005 National Health Interview Survey (NHIS) data from the US. Our results are split by gender, and we find that there are distinct differences between males and females in terms of factors which impact on obesity. Additionally we find that the WHO boundary classifications may indeed be inappropriate at the margin for certain groups of individuals.

2 Econometric Framework

We follow the existing literature in assuming that an individual's BMI is an *ordinal*, not a *cardinal*, representation of their weight-related health status (see, for example, Andreyeva, Michaud, and Van Soest 2005, Sanz-de Galdeano 2005). In other words, we will assume that there is not a one-to-one relationship between BMI levels and weight-related health status levels. We therefore translate observed BMI values into an ordinal scale. This approach enables us to preserve the underlying ordinal nature of the BMI index, while at the same time recognizing that individuals within a so-defined BMI-category are of an approximately equivalent weight-related health status level. The $j = 0, \ldots, J$ categories are defined as: normal weight, overweight and obese[2].

[2]We remove the underweight (BMI $<$ 18.5) so an increase in j unambiguously represents a worsening of weight-related health status. Also, in policy terms we are concerned with those who are categorized inappropriately as overweight/obese: it is difficult to interpret who would be classified as "inappropriately underweight" in our sample. The underweight amounted to less than 2 per cent of the sample.

The existing empirical literature on the socioeconomic determinants of obesity typically estimate discrete choice models to examine which factors, individual and/or behavioral, are correlated with obesity levels. Thus following Zavoina and McElvey (1975), (Zavoina and McElvey 1975) the usual way to model such discrete, ordered data would be to employ ordered probit, (or logit) models. This will form the benchmark model in our econometric analysis. The ordered probit (OP) model is usually justified on the basis of an underlying latent variable, y^* which is a linear (in unknown parameters, $\boldsymbol{\gamma}$) function of a vector of observed characteristics, $\mathbf{z}$, and its relationship to certain boundary parameters, $\boldsymbol{\mu}$. We can therefore write

$$y^* = \mathbf{z}'\boldsymbol{\gamma} + u, \tag{1}$$

which is related to the observed outcome y, here defined to be the BMI category ($j = 0, \ldots, J$) as

$$y = \begin{cases} 0 & \text{if } y^* \leq 0, \\ j & \text{if } \mu_{j-1} < y^* \leq \mu_j, \;\; for \; 0 < j < J \\ J & \text{if } \mu_{J-1} \leq y^*, \end{cases} \tag{2}$$

with, under the assumption of normality, associated probabilities (Maddala 1983) of

$$\Pr(y) = \begin{cases} \Pr(y = 0|\mathbf{z}) & = & \Phi(\mu_{j=0} - \mathbf{z}'\boldsymbol{\gamma}) \\ \Pr(y = j|\mathbf{z}) & = & \Phi(\mu_j - \mathbf{z}'\boldsymbol{\gamma}) - \Phi(\mu_{j-1} - \mathbf{z}'\boldsymbol{\gamma}); \;\; for \; 0 < j < J \\ \Pr(y = J|\mathbf{z}) & = & 1 - \Phi(\mu_{J-1} - \mathbf{z}'\boldsymbol{\gamma}), \end{cases} \tag{3}$$

with the implicit assumption, maintained throughout, that $\mu_{j=0} = 0$.

Irrespective of which observed category an individual belongs to, the individual can be thought of belonging to one of two, or indeed more, classes. Some of these individuals will inherently, perhaps due to time-invariant, or "fixed", characteristics such as genetics[3], be a part of a particular observed BMI-category while others will be a part of the same observed category due to other factors, for example, lifestyle factors and behavioral choices. These two distinct sets of individuals are likely to

[3] A recent study in *Science* states that an obesity predisposing geno-type is present in 10% of individuals(Herbert, Gerry, and McQueen 2006). Given 25-26% of our sample are categorised as obese, this supports the hypothesis that other factors impact upon the probability of being obese.

have completely different reaction curves to various different policy measures and not taking this inherent decomposition into account could result in biased estimates.

Thus while the standard OP model forms the basis of our modeling strategy, we will also follow the growing literature on modeling health outcomes by utilizing a latent class approach (see, for example, Deb and Trivedi 2002, Bago D'Uva 2005b, Bago D'Uva 2005a). We will restrict ourselves to the two class finite mixture model, for several reasons. Empirically, these tend to be the most favored models and any wider choice renders interpretation of the classes much more difficult. Also, the parametric models become very large and unwieldy with too many latent classes, and with a two class finite mixture model we can relatively easily take into account the likely correlation between the two implicit equations driving class membership and observed BMI-category outcomes. Moreover, the two classes could be conveniently interpreted as inherently obese (class 1), or inherently non-obese (class 0), with respect to a set of "fixed" characteristics (such as country of birth, ethnic origin and age).

Formally, we define a latent variable c^* which determines latent class membership. This is assumed to be a function of a vector of observed characteristics $\mathbf{x}$, with unknown weights $\boldsymbol{\beta}$ and a random disturbance term ε such that

$$c^* = \mathbf{x}'\boldsymbol{\beta} + \varepsilon. \tag{4}$$

Under the usual assumption of normality, the probability of an individual belonging to class 1 (and one minus this for class 0) is given by

$$\Pr(c = 1|\mathbf{x}) = \Pr(c^* > 0|\mathbf{x}) = \Phi(\mathbf{x}'\boldsymbol{\beta}), \tag{5}$$

where $\Phi(.)$ is the cumulative distribution function (*c.d.f.*) of the univariate standard normal distribution.

Of course, neither c^*, nor indeed c, are observed. The latent class framework here states that *conditional* on being in class 0 or 1, outcomes are then determined by the relevant OP model (of equations of (1) and (2)): that is, two different OP equations, one for each class. In this way observed characteristics can have differing marginal effects on the outcomes for the two different latent classes. For example, changing exercise levels may have different effects for those who are inherently obese as compared to those who are not.

The overall probability of an outcome ($j = 0, \ldots, J$) is simply the sum of those from the two respective latent classes. So, combining probabilities of the form (3) and (5) yields final probabilities of the form

$$\begin{aligned} \Pr(y = j|\mathbf{x}, \mathbf{z}) = \Pr(c = 0|\mathbf{x}) \Pr(y = j|\mathbf{z}, c = 0) \\ + \Pr(c = 1|\mathbf{x}) \Pr(y = j|\mathbf{z}, c = 1). \end{aligned} \tag{6}$$

So, for those belonging to class 0 we have

$$P_{i|c} = \begin{cases} \Pr(y = 0|\mathbf{z}, c = 0) & = & (1 - \Phi(\mathbf{x}'\boldsymbol{\beta}))[\Phi(-\mathbf{z}'\boldsymbol{\gamma}_0)] \\ \Pr(y = j|\mathbf{z}, c = 0) & = & (1 - \Phi(\mathbf{x}'\boldsymbol{\beta}))[\Phi(\mu_{0,j} - \mathbf{z}'\boldsymbol{\gamma}_0) - \Phi(\mu_{0,j-1} - \mathbf{z}'\boldsymbol{\gamma}_0)] \\ & & (0 < j < J) \\ \Pr(y = J|\mathbf{z}, c = 0) & = & (1 - \Phi(\mathbf{x}'\boldsymbol{\beta}))[1 - \Phi(\mu_{0,J-1} - \mathbf{z}'\boldsymbol{\gamma}_0)], \end{cases} \tag{7}$$

and similarly for those belonging to class 1 we have

$$P_{i|c} = \begin{cases} \Pr(y = 0|\mathbf{z}, c = 1) & = & \Phi(\mathbf{x}'\boldsymbol{\beta})[\Phi(-\mathbf{z}'\boldsymbol{\gamma}_1)] \\ \Pr(y = j|\mathbf{z}, c = 1) & = & \Phi(\mathbf{x}'\boldsymbol{\beta})[\Phi(\mu_{1,j} - \mathbf{z}'\boldsymbol{\gamma}_1) - \Phi(\mu_{1,j-1} - \mathbf{z}'\boldsymbol{\gamma}_1)] \\ & & (0 < j < J) \\ \Pr(y = J|\mathbf{z}, c = 1) & = & \Phi(\mathbf{x}'\boldsymbol{\beta})[1 - \Phi(\mu_{1,J-1} - \mathbf{z}'\boldsymbol{\gamma}_1)]. \end{cases} \tag{8}$$

However, independence of the unobservables in equations (4) and (1) (that is, ε and u) appears, *a priori*, to be an untenable assumption, as these relate to the same individuals. Thus one might expect that the unobservables driving class membership will be positively correlated with those driving observed BMI category for an inherently obese class; and *vice versa* for those in an inherently non-obese class: all other things equal, the more likely an individual is to be in the non-obese class, the lighter they will be (and again, *vice versa*). In light of this, we allow ε and u to be correlated, with respective correlation coefficients ρ_0 and ρ_0.

So here, the respective probabilities are no longer independent, but a function of bivariate normal *c.d.f.*s, for which accurate approximations exist. Therefore, for membership in class 1 ($c = 1$), the probabilities can be written as

$$\Pr(y=j|c=1)=\begin{cases}\Pr(y=0|c,\mathbf{z}) & = & \Phi_2(\mathbf{x}'\boldsymbol{\beta},-\mathbf{z}'\boldsymbol{\gamma}_1;-\rho_1)\\ \Pr(y=j|c,\mathbf{z}) & = & \Phi_2(\mathbf{x}'\boldsymbol{\beta},\mu_{1,j}-\mathbf{z}'\boldsymbol{\gamma}_1;-\rho_1)\\ & & -\Phi_2(\mathbf{x}'\boldsymbol{\beta},\mu_{1,j-1}-\mathbf{z}'\boldsymbol{\gamma}_1;-\rho_1)\\ & & (0<j<J)\\ \Pr(y=J|c,\mathbf{z}) & = & \Phi_2(\mathbf{x}'\boldsymbol{\beta},\mathbf{z}'\boldsymbol{\gamma}_1-\mu_{1,J-2};\rho_1)\end{cases} \tag{9}$$

where $\Phi_2\,(a,b;\rho)$ denotes the cumulative distribution function of the standardized bivariate normal distribution with correlation coefficient ρ between the univariate random elements, while those for class 0 are

$$\Pr(y=j|c=0)=\begin{cases}\Pr(y=0|c,\mathbf{z}) & = & \Phi_2(-\mathbf{x}'\boldsymbol{\beta},-\mathbf{z}'\boldsymbol{\gamma}_0;\rho_0)\\ \Pr(y=j|c,\mathbf{z}) & = & \Phi_2(-\mathbf{x}'\boldsymbol{\beta},\mu_{0,j}-\mathbf{z}'\boldsymbol{\gamma}_0;\rho_0)\\ & & -\Phi_2(-\mathbf{x}'\boldsymbol{\beta},\mu_{0,j-1}-\mathbf{z}'\boldsymbol{\gamma}_0;\rho_0)\\ & & (0<j<J)\\ \Pr(y=J|c,\mathbf{z}) & = & \Phi_2(-\mathbf{x}'\boldsymbol{\beta},\mathbf{z}'\boldsymbol{\gamma}_0-\mu_{0,J-2};-\rho_0).\end{cases} \tag{10}$$

The log likelihood function, for a random sample of $i = 1, \ldots, N$ individuals, can be written as

$$\ell(\Theta)=\sum_{i=1}^{N}\sum_{j=0}^{J}h_{ij}\ln\left[\Pr\left(y_i=j\,|\mathbf{x}_i,\mathbf{z}_i\right)\right]=\sum_{i=1}^{N}\sum_{j=0}^{J}h_{ij}\ln\left[\sum_{c=0}^{C=1}P_{ij|c}\right] \tag{11}$$

where the indicator function h_{ij} is

$$h_{ij}=\begin{cases}1\text{ if individual } i \text{ is in outcome } j\\ 0 \text{ otherwise.}\end{cases} \quad (i=1,...,N;\;\; j=0,1,...,J). \tag{12}$$

and where $P_{ij|c}$ are the probabilities of individual i being in outcome $j = 0, \ldots, J$ conditional on class membership c.

Conditional (on $\mathbf{x}$ and $\mathbf{z}$) Maximum Likelihood estimation involves maximization of equation (11) with $\Theta = (\boldsymbol{\beta}', \boldsymbol{\gamma}_c', \boldsymbol{\mu}_c', \boldsymbol{\rho}_c')'$, with $\boldsymbol{\rho}_c' = (\rho_0, \rho_1)$. *Wald* tests of $\rho_c = 0$ are tests of independence of the two respective error terms.

Finally, attention is turned to the boundaries defining weight categories, which are those set by the WHO. It is possible that strong adherence to these may be too strict an approach in terms of defining obesity. For example, athletes may have relatively high BMI levels due to high percentages of muscle mass, rather than fat. Using such strictly defined WHO definitions may consequently “push” individuals into inappropriate categories. Moreover, as the use of cut-off points is important in terms of which set of individuals are targeted and how health promotion resources are used, how to treat the cut-off points is very important. Other variables, in addition to proxies for muscle mass levels, may combine to adjust the boundary parameters to more appropriate levels for different individuals. Furthermore, it appears appropriate to allow some flexibility at the margin of these boundary parameters: if an individual slips from being at the bottom end of the BMI obese category into the top end of the BMI overweight category, is this really an improvement in their health status?

To test these hypotheses, we consider Generalized Ordered Probit models (Pudney and Shields 2000), where the boundary parameters are functions of observed personal characteristics. However, to avoid indeterminacy with regard to common variables, here and elsewhere in the model, we adopt the parametrization that

$$\mu_{cij} = \exp\left(\theta_{cj} + \mathbf{w}_i'\boldsymbol{\delta}_c\right), \tag{13}$$

where the $\mathbf{w}_i$ are variables thought to affect the position of the boundary parameters, excluding a constant term, with unknown weights $\boldsymbol{\delta}_c$. These weights are constant across boundaries and θ_{cj} is a constant term for each boundary parameter, but one which varies across classes. That is, conditional on class, each μ has a different constant term, but the same coefficient vector, and the model reverts to the more standard setting if $\boldsymbol{\delta}_c = \mathbf{0}$. For estimation purposes, the μ's of equation (9) are replaced by those of (13) in equation (11) and Θ becomes $\Theta = (\boldsymbol{\beta}', \boldsymbol{\gamma}_c', \boldsymbol{\rho}_c', \boldsymbol{\theta}', \boldsymbol{\delta}_c')'$. The exponential function is not only convenient, in that it necessarily yields $\mu_{cij} > 0 \forall c, i, j$, but also helps in identification of $\boldsymbol{\delta}_c$.[4]

3 Data and Variable Selection

We use US data from the National Health Interview Survey (NHIS) for 2005, an annual representative cross sectional survey. The NHIS is conducted annually by the

[4]For example, such an approach is often adopted in parameterizing heteroskedastic variances.

National Center for Health Statistics (NCHS) and the Center for Disease Control and Prevention (CDC). The NHIS administers face-to-face interviews in a nationally representative sample of households. Each week a probability sample of the civilian non-institutionalized population of the US is interviewed by personnel of the US Bureau of the Census. Information is obtained about the health and other characteristics of each member of the household. Our final estimating sample consists of 15,259 females and 12,601 males. We split the sample, and subsequent estimations, by gender: initial modeling on a pooled sample showed distinct, and interesting, differences across the sexes and it was clear that analysis using this pooled sample was hiding potentially important, policy relevant, information[5]. Descriptive statistics, split by gender, are presented in Table 1.

As Table 1 shows, 31% of males and 44% of females are of normal weight (BMI $\in (18.5, 25)$), 44% of men and 30% of women are overweight (BMI $\in (25, 30)$) and 25% of men and 26% of women are obese (BMI > 30). Women in the sample are marginally older (average age of 47 compared to 46 years for males) and are more likely to be born in the US. On the other hand, they are less likely: to be married; to have parents born overseas; to exercise; to exercise vigorously; and to undertake strength or weight training exercise. Men and women have similar levels of educational attainment[6], and home ownership rates, but men are richer compared to women[7].

Our final, and most flexible, specification consists of three distinct stages: first x, a "selection" (or "splitting") stage, which divides individuals into the two latent classes; second z, conditional on class membership, estimation of two distinct OP models; and finally w, allowing the boundary parameters in these OP equations to

[5] The literature also suggests clear differences across genders with regard to obesity (see, for example, Muennig, Lubetkin, Haomiao, and Franks 2006).

[6] Education levels range from $0-21$, 1 is 1^{st} grade, 21 is Ph.D; the "average" man and woman are high school graduates.

[7] The NHIS use five different methods for income imputation and we make use of their method 1. The technical details of the imputation methods are available in the NHIS technical documentation (Schenkera, Raghunathanb, Chiua, M., Zhangb, and Cohen 2006). We use 11 standard bands ranging from \$1-4,999, proceeding in \$5,000 intervals up to \$24,999, then \$10,000 intervals to \$74,999, and finally \$75,000 and above. Given this, females are in band 6 on average (\$25,000-34,999) and males in band 7 (\$35,000-44,999).

vary at the margin. In estimation, all five distinct equations (one splitting equation, two OP equations - one for each class - and two boundary equations - one for each class) are estimated simultaneously; they are however, all a function of differing sets of explanatory variables. These are detailed below. As stated above, we estimate separate regressions for males and females.

3.1 Variables in the Splitting Equation (x)

The variables required here are akin to proxies for an individual's "fixed effect": they are constant over time, cannot be affected by the individual and reflect an individual's propensity to be inherently obese or not. The proxies used are: whether the individual was born in the US or not (BORN_US); whether a parent was born overseas or not (MF_OS); whether the respondent was white (WHITE) or black (BLACK) - the omitted category was "other"; and three broad time cohort dummies (COHORT1 and COHORT2), which were defined by the respondent's age, and respectively, corresponded to $25 - 49$ and 50+ (the omitted category was under 25). There are no data regarding parents' weight levels, a potentially good predictor of an individual's predisposition to be inherently obese or not (Von Kries, Toschke, Koletzko, and Slikker 2002, Reilly, Armstrong, Dorosty, Emmett, Ness, Rogers, Steer, and Sherriff 2005). However, to the extent that this, and any other unobserved influences, will be captured by error terms, such effects will be implicitly subsumed into the estimated error correlation coefficients between the class membership and observed BMI-category outcome equations.

3.2 Variables in the OP Equations (z)

Although we estimate two implicit OP equations, by latent class, and the same variables are included as explanatory variables in both, they have potentially differing effects across class. Here we include time-varying variables which potentially represent lifestyle choices of the individual. We include a quadratic in age - scaled by 10 (AGE10 and AGESQ10) to capture the non-linear effects of age on individuals' weight ranges. We also consider an individual's income and wealth levels. Explicitly, we have an indictor for whether the individual owns their own home (OWN); and a quadratic in income (INC and INCSQR). This latter effect is somewhat ambiguous *a priori*. Very low income families may exhibit lower BMI ranges due to low food and caloric intakes; although there may also be a tendency for these families to focus food expenditures on higher calorie dense foods.

Education levels (EDU) are included as it is hypothesized that more educated individuals will be more aware of the health risks involved with rising BMI levels. There may be a "comfort" marriage factor (Sobal, Rauschenbach, and Frongillo 2003). To capture this, we include a dummy variable (MARRY). Although we have no nutrition intake information pertaining to the individual, the survey does include information on another obvious lifestyle choice with regard to BMI levels, the duration of exercise undertaken. We include a dummy variable for participation in any moderate exercise (EXERCISE); and also an intensity measure (VIGOROUS) which is a count of the number of times the individual undertakes vigorous activity in a week.

3.3 Variables in the OP Boundary Equations ($\mathbf{w}$)

Our hypothesis here is that the WHO boundaries may be inappropriate for particular sub-groups of the population, and that it may be preferable to allow these boundaries to shift at the margin for certain groups. An obvious such group here, as mentioned above, are weight/strength trainers and athletes, who may have high BMI values due to high percentages of relatively heavy muscle mass as compared to body fat. The NHIS is ideal in this respect as the variable W_FREQ represents the number of times that the respondent weight/strength trains per week. Another candidate could be pregnancy: for obvious reasons, pregnant women might be incorrectly classified using a BMI-category. Although this information is available in the NHIS, the effective sample sizes were too small, and the length of pregnancy term was unknown.

We also tested the boundaries for one further group - after a certain age muscle mass begins to waste away, and so those over a certain age may have a higher proportion of body fat, leading to them having a lower BMI, but in fact they are not more healthy. We tested various age categories, and report the variable representing potentially retired individuals, *i.e.*, those aged 62 or above[8].

4 Results

The various regression results are presented in Tables 2 and 3 for the sample of males and females, respectively. The three stages above (corresponding to the $\mathbf{x}$, $\mathbf{z}$ and $\mathbf{w}$ covariates) are reported, and within each of these, five sets of results (Models $1-5$) are presented for comparison purposes. Model 1 presents the standard OP regression results where we account for neither the latent classes (no splitting parameters are estimated), nor do we allow the boundary parameters to depend on individual characteristics. Model 2 is the latent class OP (LCOP), which accounts for the latent classes (splitting parameters are estimated) but does not allow the unobservables in the two equations (ε and u) to be correlated, *i.e.*, $\rho_c = 0; c = 0, 1$. Additionally we do not allow the boundary parameters to depend on individual characteristics. Model 3 is the latent class generalized ordered probit (LCGOP) model where we allow the boundary parameters to depend on individual characteristics, but do not allow the unobservables in the two equations (ε and u) to be correlated: $\rho_c = 0; c = 0, 1$. Model 4 is the latent class correlated ordered probit (LCCOP) model where we allow for cross equation correlation (*i.e.*, allow for the possibility that $\rho_c \neq 0; c = 0, 1$) but we do not allow the boundary parameters to depend on individual characteristics. Finally Model 5 is the complete model (latent class correlated generalized ordered probit model - LCCGOP): here we allow for cross equation correlation and also allow the boundary parameters to depend on individual characteristics. Our discussion here will focus on the results corresponding to Model 5 (LCCGOP). This is the favoured model both statistically and on *a priori*

[8]This reflects the age at which an individual can begin to collect a portion of social security retirement benefits in the US. Moreover, the results were essentially invariant to the choice of discontinuity at age 62, 65 or 70.

grounds.

As with all discrete choice models, the parameter values themselves, with respect to the covariates, are somewhat meaningless. Therefore, full marginal effects and their associated standard errors, corresponding to the specifications of Model 5 are presented in Table 5. It is important to note that for the results presented in Tables 2 and 3 the set of explanatory variables in the three equations (4), (1) and (13) are mutually exclusive according to our priors. The model results are robust under the various specifications[9].

In this bivariate model, it is not possible to compute the posterior class probabilities independently from the choice probabilities. It is in this way that the classes are usually labelled. However, it is possible to compute (post-estimation), for each individual, the probabilities of them being in each BMI-category by class, using the expressions in equations (9) and (10). Averaging these over individuals yields the average outcome probabilities presented in Table 4. From these it is clear that for class 0 the probabilities are skewed away from being in the BMI obese category (probabilities of being obese are 0.046 for men and 0.069 for women in class 0, compared to 0.312 and 0.412 to be in the BMI normal weight category). Conversely, average probabilities in class 1 are skewed towards being in the BMI obese category (average outcome probabilities 0.200 and 0.194 to be in the BMI obese category for men and women, compared to 0.003 and 0.028 to be in the BMI normal weight category for those in class 1). In light of this, we will refer to class 0 as "inherently non-obese", and class 1 as "inherently obese" (in BMI classification terms).

4.1 Splitting Equation (x)

As can be seen in stage 1 (the $\mathbf{x}-$variables and the splitting function parameters in Tables 2 and 3), the latent class equation determining class membership *i.e.* whether inherently non-obese (class 0), or obese (class 1), is affected by: being born in the US; mother or father being born overseas for females; year of birth cohort (CO-

[9]Results available from the authors on request.

HORT1 and COHORT2); and ethnicity (although interestingly the coefficient on BLACK is negative for males, and positive for females). These are generally consistently significant across all models for both males and females. These variables dictate the latent classes – they are largely speaking genetic or pre-determined: an individual cannot change these variables of origin. In terms of defining class membership, a positive coefficient means that this attribute makes the individual more likely to be in class 1 (inherently obese) and *vice versa*. For example, the two cohort variables are significant and positive for both genders, relative to the omitted variable (chronologically the first time period cohort), suggesting that individuals have become more inherently obese over time. This finding is consistent with the finding that obese parents are more likely to have children with weight problems, potentially contributing to the rise in numbers of inherently obese over time (Von Kries, Toschke, Koletzko, and Slikker 2002, Reilly, Armstrong, Dorosty, Emmett, Ness, Rogers, Steer, and Sherriff 2005). These latent class results also suggest that, across genders, those born in the US are more likely to be inherently obese than those who were not.

4.2 OP Equations (z)

For the second stage (corresponding to the $\mathbf{z}-$variables and the OP coefficient estimates in Tables 2 and 3), observed BMI-category within class models, again concentrating on the full model (model 5), we see the effects of lifestyle factors and choices on observed BMI-category, conditional on class membership. Interestingly, from a policy perspective, both males and females in the inherently non-obese class (class 0), appear much more responsive to lifestyle factors and choices than those in the inherently obese class (as evidenced by significance levels). This suggests that policy aimed at reducing obesity levels will be more effective if targeted to those inherently non-obese.

We find for both genders and classes, age is associated with an increasing BMI-category, whereas age squared is associated with a decrease in such. Thus there is a clear $n-$shaped relationship between BMI levels and age, regardless of gender or latent class[10]. For females, we find being married has a negative effect on BMI-category in class 1 (the inherently obese) and a positive effect in class 0. For males there is a "comfort" marriage factor across both classes, but it is only significant for class 0.

For males and females, education is negatively associated with BMI-category, *i.e.* the higher the level of educational attainment, the lower an individual's BMI is likely to be. This effect occurs not only across genders, but also across all latent classes. For females and males in class 0, income is associated with increased BMI-category, and income squared is negative. This $n-$shaped effect of income for the inherently non-obese, may be an effect of earned and unearned income. An increase in earned income may have an effect in terms of increased weight if the job is sedentary. An increase in unearned income may not impact on physical activity levels. If initial levels of income are generated through sedentary jobs, and very high income levels are generated from unearned income this would help partially explain our findings[11]. An unearned income effect may be dominant in developed countries, especially for females (Lakdawalla and Philipson 2002).

Home ownership is only positive and significant for males in class 0. This may reflect affluence, or wealth, levels. Home ownership is often used in this way and is more stable than income at measuring cumulative prosperity (Laaksonen, Sarlio-Laĺhteenkorva, and Lahelma 2004). From a policy perspective, it is interesting that exercise in general, has a significantly negative effect on BMI-category for class 1 (inherently obese) males and females, perhaps signifying that some exercise helps reduce observed BMI-category. However, it apparently has no effect on such categories for the inherently non-obese. Exercise intensity (vigorous exercise) however, has a negative effect on BMI-categories, but only for the class 1 males and class 0 females.

[10] We consider the relative magnitudes of these, across class and gender, below.

[11] Unearned income could be across the range of income, for example from transfer payments for rich or poor.

4.3 Boundary Equations (w)

In stage 3 (corresponding to the $\mathbf{w}-$variables, in Tables 2 and 3), the boundary parameter estimates include two variables: frequency of weight training and a dummy for those aged 62 and over. There are no effects in class 1 for males or females. That is, for the inherently obese, there appear to be no boundary effects at the margin. However, we find that W_FREQ is significant for men in class 0 and positively related to BMI. So if the boundaries are allowed to vary these individuals would be more appropriately classified, as boundaries are allowed to shift up. For males in class 1 being over 62 is also positively and significantly associated with an increased BMI, so individuals being retirement age or above may also be more appropriately classified by shifting boundaries. These results essentially imply that the rigid WHO boundaries appear to be inappropriate for these identified groups, at least for the individuals who are not inherently obese.

4.4 Predicted Probabilities and Marginal Effects

It is useful to interpret the results in terms of probabilities. In Figures $1-4$ we present the probability profiles, as the continuous variables vary across the three WHO defined weight categories - normal, overweight and obese. Once more, these are evaluated using the probability expressions defined by equations (9) and (10), replacing unknown parameters by their estimated values and holding all other explanatory variables (except for the one under consideration) at their sample means. We consider the overall probability of each BMI-category, and also its inherent decomposition into its two component classes.

Note that for all profiles, for all the factors considered (age, income, education and weight training), the total probabilities of being in the normal BMI-category are dominated by those in the non-obese class (class 0). This is so much so, that there is essentially a zero probability of an inherently obese individual being in the normal BMI-category, no matter what the configuration of the explanatory variables. At the other extreme, the probabilities of being in the obese BMI-category, are always heavily dominated by those in the inherently obese class (class 1). However, depending on the configuration of the explanatory variables under consideration, the probability of an inherently non-obese individual being in this category can be clearly non-zero. Finally, typically the shape of all three profiles (total, class 1 and class 0) generally follow a similar profile.

Turning first to age (Figure 1), we find that the effects are similar for males and females. As noted there is effectively zero probability of class 1 (inherently obese) being in the normal BMI-category. For those in class 0, there is a distinct $u-$shape, with the nadir of the probability profile occurring around the late forties to early fifties. For males in the overweight BMI-category, there is a clear $n-$shape in the probability profile, augmented at age 62 by the boundary parameter effect. As expected *a priori*, individuals in this post-retirement age are less likely to be classified as obese due to a deterioration of muscle mass. These overall probabilities are again dominated by class 0. Males appear to be at the greatest risk of being overweight from their late forties to early seventies. The probability profiles for females in this category exhibit some distinct differences from their male counterparts. Firstly, class 1 probabilities contribute much more to the totals (although these are still dominated by the inherently non-obese probabilities). Secondly, overall probabilities effectively monotonically increase for the range of ages considered, and there is only a damped $n-$shaped profile in the class 0 probabilities. Turning to the obese BMI-category, for males a dampened $n-$shaped profile exists in total probabilities. As noted above, this total is dominated by probabilities corresponding to the inherently obese latent class. Here, there is a distinct drop in the probability of obesity post retirement age. A more pronounced $n-$shape is evidenced for total female probabilities, although the post-retirement boundary effect is virtually nil. For both males and females, obesity probabilities appear to be at a zenith in the (approximate) age band late forties to early fifties, and overall probabilities for the latter are marginally higher.

Figure 2 shows the effect of increases in years of education. For the normal BMI-category, there is a clear gradient for both men and women and one which is significantly steeper for the latter: as the individual's education increases, so does the likelihood that they will be of normal BMI-category weight. For both genders, the probability profiles for the overweight BMI-category appear somewhat invariant to education levels. However, at high levels of education, probabilities here for the inherently obese latent class tend to rise somewhat, hence the total and class 0 profiles diverge somewhat. Finally, increased education levels clearly reduce obesity probabilities: an effect which is much more pronounced for females.

There appears to be little curvature for male probabilities with respect to income (Figure 3): normal probabilities decrease slightly with income, whereas overweight and obese probabilities rise marginally. For females, there is a much more pronounced $u-$shape profile in income with respect to the normal BMI-category probabilities. We witness an initial decreasing of probabilities at low income levels, which then increases with higher levels, increasing above initial levels from income band 7 onwards ($35,000-44,999). As with males, overweight probabilities are little affected by income, although class 0 ones do tend to fall away at income levels. Markedly different from their male counterparts, obese probabilities decrease at higher income levels, again the difference being more pronounced above income band 7. As noted above, one reason for these income effects may be differences in earned and unearned incomes.

Finally, turning to hours spent weight-training (Figure 4), we see that this has no effect of the normal BMI-category, as this first boundary parameter has been normalized to zero. For males, there is a sharp increase (decrease) in the probability of being in the overweight (obese) BMI-category for low levels of strength training, although this effect dies out after about five hours. For women, these effects are much more pronounced, although recall that these were much less precisely estimated. Thus, as hypothesized, weight-trainers are less likely to be classified as obese.

Further information is elicited when we look at the marginal effects, by BMI-category, presented in Table 5[12]. We pick out several interesting marginal effects. For example, when looking at the boundary variables for males, for both weight

[12] These were obtained by numerically evaluating the derivatives of the probabilistic expressions with respect to the covariates. Standard errors were obtained by the delta method.

training and being over 62, marginal effects are significantly positive for the overweight and negative for the obese. The probability of being obese is, significantly, 16 percentage points (pp) higher if born in the US for men, and 11 pp higher for women. White females are 7 pp less likely to be obese, while black females are 5 pp more likely. There is a 'comfort' marriage factor for men, with a probability of being obese 3 pp higher. Married individuals, both men and women, are more likely to be overweight. Males and females who undertake some exercise are 2-4 pp less likely to be obese, this is confirmed when looking at the marginal affects split by class, see Table 7 for class 1.

It is also possible to decompose these overall marginal effects into those arising from the two implicit classes. For example, consider the overall significant marginal effect for males if born in the US: 15.8 pp. However, this consists of a significantly negative effect (of -0.5 pp) from class 0 (the inherently non-obese class) combined with a significantly positive effect (of 16.3 pp) for those in class 1 (see Tables 6 and 7). The age cohort also impacts on the marginal effects, being negative, but almost zero to be in the obese category for class 0, and positive, but between 4 and 7 pp more likely to be in the obese category for the older cohort for class 1 individuals. In this way, superficially insignificant variables, may, in fact, be important. Consider, finally, the exercise variable for women. We would expect this to have a negative effect on obesity BMI-categories and a positive effect on normal categories. However, the overall marginal effect for women (Table 5) suggests that exercise only affects obesity probabilities. However, this somewhat disguises the fact that for the inherently non-obese this has no significant effect (Table 6), while for the inherently obese (class 1) exercise still has a significantly negative marginal effect with regard to obesity BMI-category, but also significantly positive and negative effect on overweight and normal weight BMI-categories, respectively. This highlights the fact that basing policy on solely the overall marginal effects may be misleading: in this instance, exercise can, indeed, be effective in increasing normal BMI-category probabilities.

5 Conclusions

We extend the discrete data latent class literature by explicitly defining a latent variable for class membership as a function of both observables and unobservables, thereby allowing the equations defining class membership and observed outcomes to be correlated. The procedure is applied to modeling observed obesity outcomes, based upon an underlying ordered probit equation. We hypothesize that the World Health Organization boundaries for converting BMI into weight categories may be inappropriate for individuals at the margin. To allow for this in estimation, we additionally allow the inherent boundary parameters of the ordered probit equation to vary by observed characteristics.

We find strong evidence for the presence of the latent classes, based on pre-determined characteristics. BMI-categories are significantly determined by lifestyle characteristics, and we find that fixed boundary parameters may be inappropriate for at least two distinct groups: those who weight-train and those over 62 (*i.e.*, of a retirement age), but these effects only hold for the inherently non-obese latent class.

Our results have important policy implications, in terms of targeting resources. For example those who are in class 0, and who are obese may be more usefully targeted in terms of policies which impact on behavioral effects, as they are less likely to be inherently obese. Those in class 1 may be more effectively targeted using medical interventions, as it may be less likely to be lifestyle or behavioral factors which impact upon the probability of being obese. In general, it appeared that those inherently obese were much less responsive to lifestyle factors and choices.

However, some interventions, for example basic exercise, or increasing income/education may impact upon either latent class. The probability of being obese is greater for those who are married, and higher levels of education are associated with lower levels of obesity. Exercise is significant for individuals in the inherently obese class. Increased levels of unearned income for males may help reduce obesity by reducing predominantly sedentary time spent earning income. The effects of the wealth variable may also reflect this.

These results, and models of this type, may help targeting of health promotion. For example our results may imply those with higher education levels understand health education concerning obesity, so perhaps messages could be more effectively targeted at those with lower education levels. Targeting of married individuals may also be useful, as may the targeting of those born in the US (as compared to those born overseas), although a better breakdown of ethnic origin would help targeting more. The inherently obese latent class were relatively unresponsive to lifestyle factors and choices, so perhaps medical interventions would be more usefully targeted at this class.

Finally, the WHO boundaries may be inappropriate for categorizing certain individuals as obese, those over 62, and intensive weight-trainers in the inherently non-obese male class being the two examples we highlight here. There may be other groups, for example pregnant women, where this may also be relevant. More flexibility in the boundaries will allow a more accurate assessment of who really is obese, even helping somewhat to overcome perceived deficiencies in using BMI as the measure of obesity, and therefore who should be targeted in terms of scarce public health and health education resources.

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Figure 1: Probability Profiles: Age

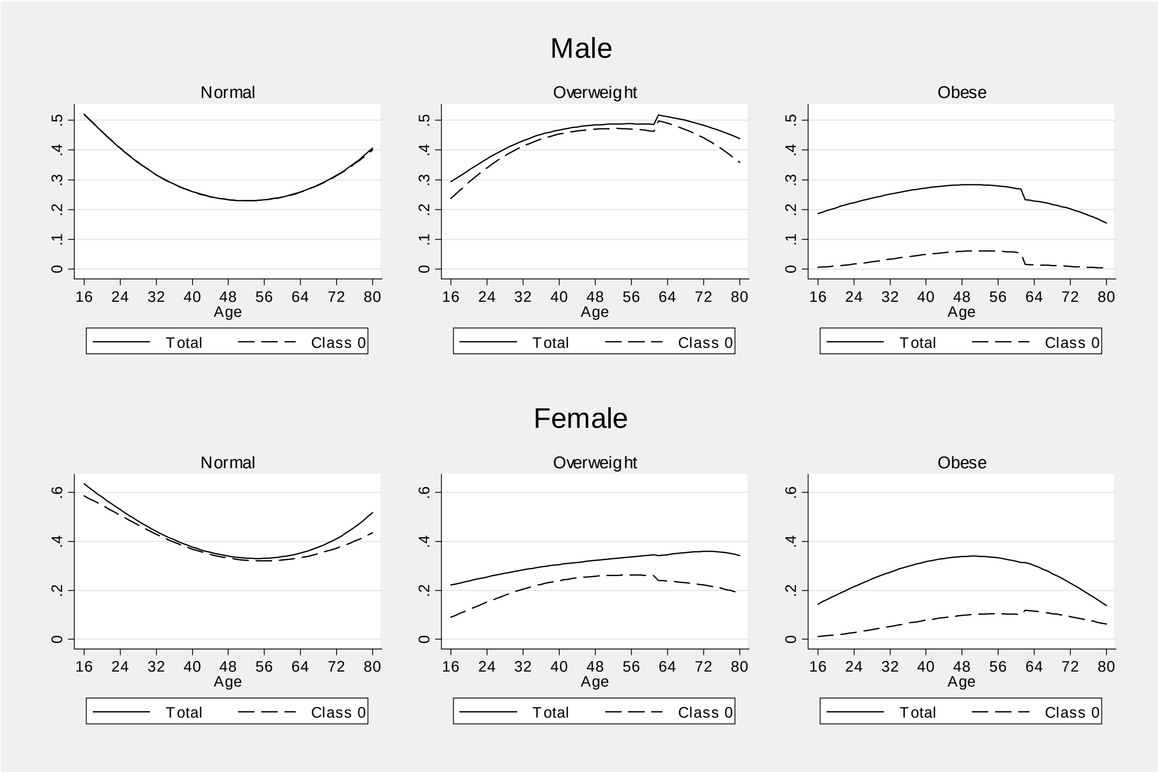

Figure 2: Probability Profiles: Years of Education Attained

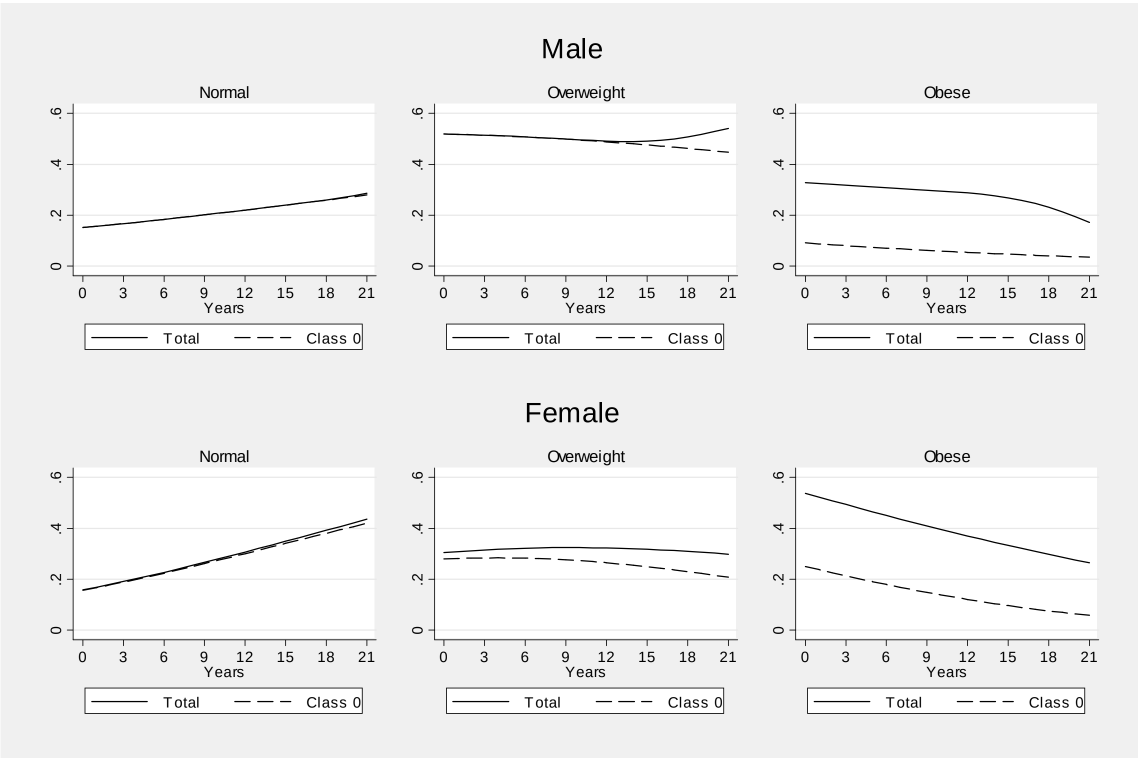

Figure 3: Probability Profiles: Income

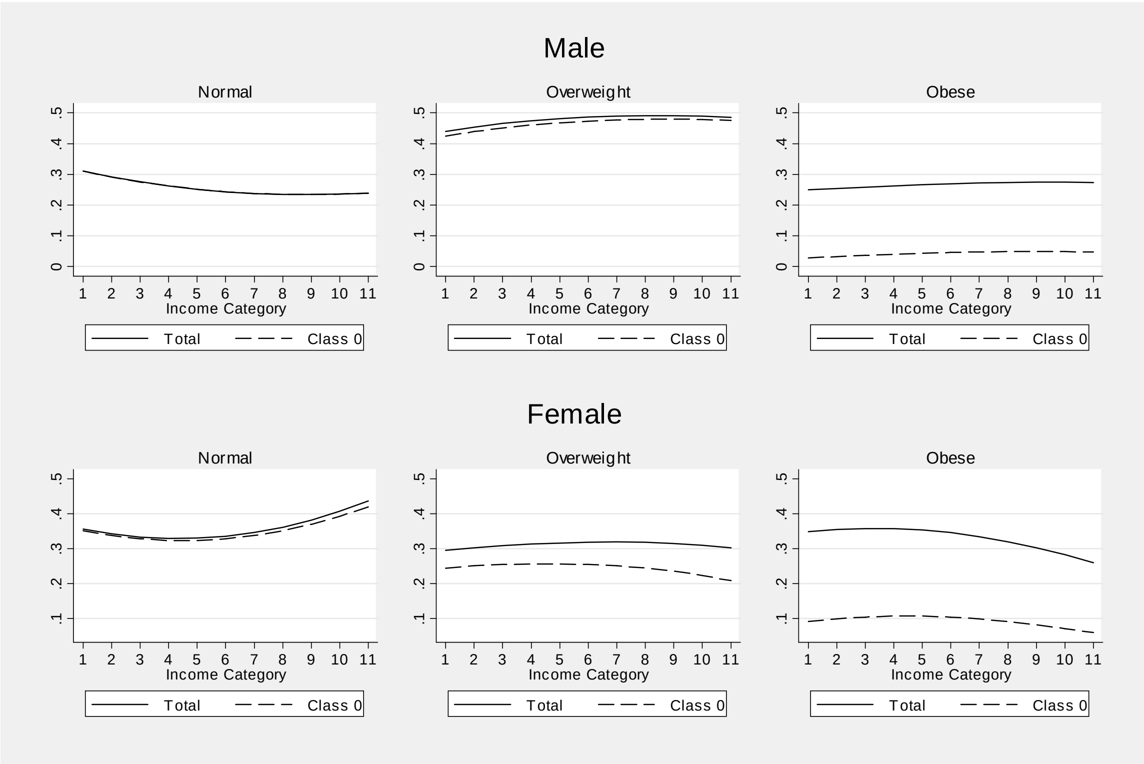

Figure 4: Probability Profiles: Hours of Weight Training

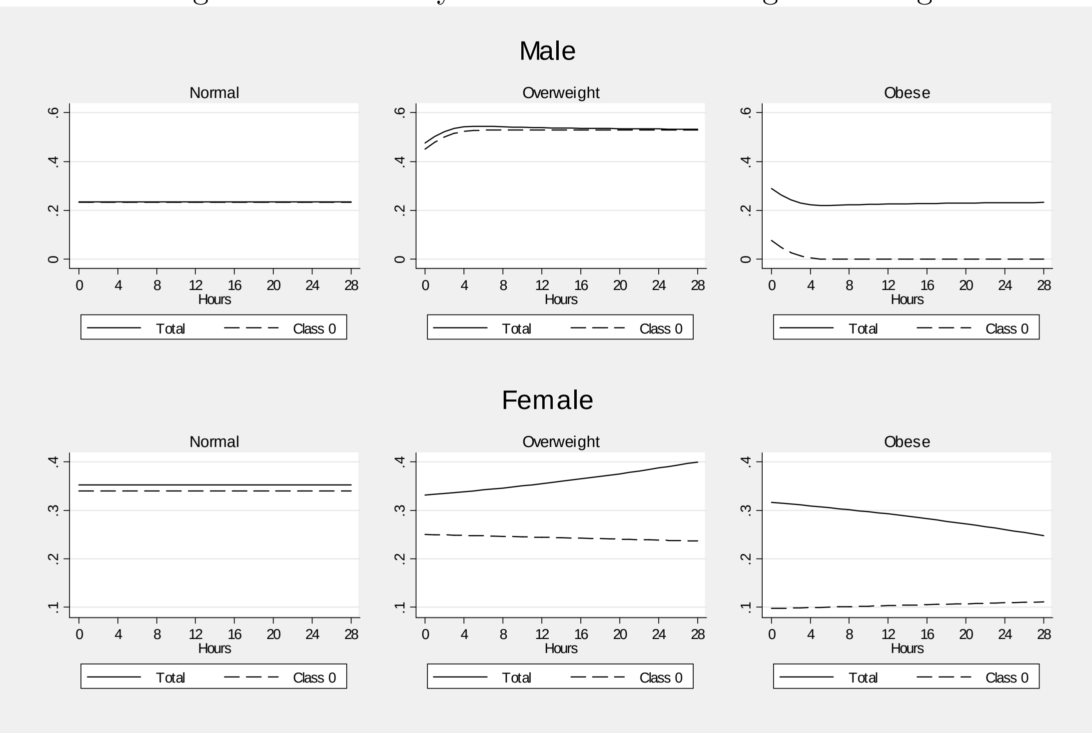

Table 1: Descriptive Statistics

		Male Sample	**Female Sample**
Sample Size		12601	15259
Variable	**Description**	**Mean**	**Mean**
W_FREQ	Duration of strength (weight training) exercise	1.0081	0.7329
		(2.3776)	(2.0996)
OVER_62	= 1 if $62 \leq$ age	0.2024	0.2323
		(0.4018)	(0.4223)
BORN_US	= 1 if born in the US	0.8144	0.8277
		(0.3888)	(0.3776)
MF_OS	= 1 if mother or father born overseas	0.0329	0.0211
		(0.1785)	(0.1437)
AGE10	Age/10 (scaled for convergence)	4.6176	4.7362
		(1.6987)	(1.7917)
WHITE	= 1 if Caucasian	0.6603	0.6331
		(0.4736)	(0.4820)
BLACK	= 1 if African American	0.1227	0.1542
		(0.3281)	(0.3612)
COHORT1	= 1 if $25 <$ age ≤ 50	0.4965	0.4798
		(0.5000)	(0.4996)
COHORT2	= 1 if age > 50	0.3820	0.4047
		(0.4859)	(0.4909)
MARRY	= 1 if Married	0.5526	0.4815
		(0.4972)	(0.4997)
INC	Income Category	7.2651	6.6591
		(3.0711)	(3.1557)
EDU	Years of Schooling	14.6215	14.4829
		(3.5563)	(3.4776)
OWN	= 1 if own house	0.6486	0.6430
		(0.4774)	(0.4791)
EXERCISE	= 1 if conducted moderate exercise in the last week	0.4315	0.3270
		(0.4953)	(0.4691)
VIGOROUS	= number of times vigorous exercise undertaken in the last week	1.6084	1.2342
		(2.9412)	(2.6480)

Standard Deviations in Parenthesis

Table 2: Regression Results: Male Sample

	Model 1	Model 2	Model 3	Model 4	Model 5
Splitting Function Parameters					
CON	-	-1.517	-1.184	-1.650	-1.318
	-	(0.13)**	(0.10)**	(0.13)**	(0.094)**
BORN_US	-	0.815	0.635	0.852	0.656
	-	(0.11)**	(0.07)**	(0.12)**	(0.08)**
MF_OS	-	0.037	0.061	0.041	0.058
	-	(0.11)	(0.10)	(0.11)	(0.10)
WHITE	-	-0.230	-0.173	-0.244	-0.173
	-	(0.07)**	(0.05)**	(0.07)**	(0.06)**
BLACK	-	-0.110	-0.078	-0.124	-0.078
	-	(0.08)	(0.06)	(0.08)	(0.07)
COHORT1	-	0.189	0.207	0.192	(0.24)
	-	(0.07)**	(0.07)**	(0.07)**	(0.07)**
COHORT2	-	0.029	0.162	0.010	0.182
	-	(0.09)	(0.09)*	(0.09)	(0.08)**
Ordered Probit Coefficient Estimates. Regime 0					
CON	-0.938	-1.708	-1.812	-1.699	-1.793
	(0.09)**	(0.14)**	(0.16)**	(0.13)**	(0.15)**
AGE10	0.615	0.759	0.790	0.756	0.785
	(0.03)**	(0.05)**	(0.06)**	(0.05)**	(0.06)**
AGESQ10	-0.061	-0.071	-0.075	-0.071	-0.075
	(0.00)**	(0.00)**	(0.01)**	(0.00)**	(0.01)**
MARRY	0.159	0.261	0.259	0.249	0.257
	(0.02)**	(0.03)**	(0.03)**	(0.03)**	(0.03)**
INC	0.062	0.067	0.075	0.067	0.077
	(0.02)**	(0.02)**	(0.02)**	(0.02)**	(0.02)**
INCSQR	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**
EDU	-0.018	-0.016	-0.023	-0.016	-0.024
	(0.00)**	(0.00)**	(0.01)**	(0.00)**	(0.00)**
OWN	0.092	0.115	0.136	0.099	0.123
	(0.02)**	(0.03)**	(0.04)**	(0.03)**	(0.03)**
EXERCISE	-0.056	0.033	0.029	0.016	0.019
	(0.03)**	(0.04)	(0.04)	(0.04)	(0.04)
VIGOROUS	-0.006	-0.005	-0.003	-0.004	-0.004
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
μ	1.204	1.529	-	1.469	-
	(0.01)**	(0.06)**	-	(0.05)**	-
Panel C: Boundary Parameters. Regime 0					
θ	-	-	0.550	-	0.518
	-	-	(0.06)**	-	(0.05)**
W_FREQ	-	-	0.142	-	0.128
	-	-	(0.07)**	-	(0.05)**
OVER_62	-	-	0.281	-	0.253
	-	-	(0.14)**	-	(0.11)**
ρ_0	-	-	-	-0.1516	-0.152
	-	-	-	(0.16)	(0.18)

Table 2. Regression Results. Male Sample (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5
Panel D: Ordered Probit Coefficient Estimates. Regime 1					
CON	-	5.804	2.610	5.797	2.655
	-	(1.23)**	(0.74)**	(3.66)	(1.61)*
AGE10	-	0.793	0.793	0.774	0.742
	-	(0.30)**	(0.21)**	(0.37)**	(0.24)**
AGESQ10	-	-0.099	-0.089	-0.100	-(0.08)
	-	(0.03)**	(0.02)**	(0.04)**	(0.03)**
MARRY	-	-0.208	0.184	-0.215	0.175
	-	(0.18)	(0.11)*	(0.20)	(0.11)
INC	-	0.036	0.081	0.019	(0.00)
	-	(0.12)	(0.07)	(0.12)	(0.07)
INCSQR	-	-0.002	-0.004	-0.001	0.001
	-	(0.01)	(0.00)	(0.01)	(0.01)
EDU	-	-0.266	-0.140	-0.314	-0.170
	-	(0.05)**	(0.03)**	(0.14)**	(0.05)**
OWN	-	-0.306	-0.096	-0.347	-0.104
	-	(0.19)	(0.12)	(0.23)	(0.12)
EXERCISE	-	-0.898	-0.428	-0.896	-0.427
	-	(0.25)**	(0.14)**	(0.44)**	(0.18)**
VIGOROUS	-	-0.038	-0.027	-0.044	-0.027
	-	(0.02)*	(0.01)*	(0.03)	(0.01)*
μ	-	1.460	-	1.445	-
	-	(0.29)**	-	(0.68)**	-
Panel E: Boundary Parameters. Regime 1					
θ	-	-	0.329	-	0.337
	-	-	(0.29)	-	(0.42)
W_FREQ	-	-	-0.018	-	-0.024
	-	-	(0.02)	-	(0.02)
OVER_62	-	-	-0.057	-	-0.081
	-	-	(0.19)	-	(0.18)
ρ_1	-	-	-	0.7572	0.699
	-	-	-	(0.34)**	(0.31)**
Sample Size	12601	12601	12601	12601	12601
Max-L	13168.210	12998.772	12996.130	13001.395	12998.143

Notes:

Standard errors in parenthesis. Significance: **: 1%; *: 5%

Model 1: Ordered Probit

Model 2: Latent Class Ordered Probit

Model 3: Latent Class Generalized Ordered Probit

Model 4: Latent Class Correlated Ordered Probit

Model 5: Latent Class Correlated Generalized Ordered Probit

Table 3: Regression Results: Female Sample

	Model 1	Model 2	Model 3	Model 4	Model 5
Splitting Function Parameters					
CON	-	-0.933	-0.799	-1.181	-1.069
	-	(0.17)**	(0.17)**	(0.18)**	(0.19)**
BORN_US	-	0.747	0.709	0.644	0.640
	-	(0.09)**	(0.09)**	(0.09)**	(0.10)**
MF_OS	-	0.299	0.301	0.296	0.291
	-	(0.13)**	(0.13)**	(0.12)**	(0.14)**
WHITE	-	-0.479	-0.462	-0.450	-0.434
	-	(0.07)**	(0.07)**	(0.07)**	(0.14)**
BLACK	-	0.338	0.353	0.294	0.326
	-	(0.07)**	(0.08)**	(0.07)**	(0.08)**
COHORT1	-	0.241	0.237	0.228	0.226
	-	(0.08)**	(0.08)**	(0.07)**	(0.07)**
COHORT2	-	0.450	0.441	0.413	0.402
	-	(0.12)**	(0.12)**	(0.11)**	(0.11)**
Ordered Probit Coefficient Estimates. Regime 0					
CON	-0.817	-1.452	-1.591	-1.514	-1.666
	(0.08)**	(0.23)**	(0.26)**	(0.22)**	(0.24)**
AGE10	0.733	0.722	0.750	0.721	0.778
	(0.03)**	(0.09)**	(0.09)**	(0.09)**	(0.10)**
AGESQ10	-0.070	-0.061	-0.063	-0.065	-0.070
	(0.00)**	(0.01)**	(0.01)**	(0.01)**	(0.01)**
MARRY	-0.041	0.156	0.179	0.127	0.132
	(0.02)*	(0.05)**	(0.06)**	(0.04)**	(0.04)**
INC	0.031	0.069	0.075	0.066	0.074
	(0.01)**	(0.03)**	(0.03)**	(0.02)**	(0.02)**
INCSQR	-0.005	-0.008	-0.008	-0.008	-0.008
	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**
EDU	-0.035	-0.053	-0.055	-0.044	-0.047
	(0.00)**	(0.01)**	(0.01)**	(0.01)**	(0.01)**
OWN	-0.031	-0.028	-0.032	-0.027	-0.033
	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)
EXERCISE	-0.169	0.011	0.063	-0.043	-0.031
	(0.03)**	(0.08)	(0.09)	(0.05)	(0.06)
VIGOROUS	-0.019	-0.072	-0.090	-0.047	-0.057
	(0.00)**	(0.02)**	(0.02)**	(0.01)**	(0.01)**
μ	0.826	1.006	-	1.012	-
	(0.01)**	(0.07)**	-	(0.09)**	-
Panel C: Boundary Parameters. Regime 0					
θ	-	-	0.073	-	0.080
	-	-	(0.10)	-	(0.10)
W_FREQ	-	-	-0.016	-	-0.003
	-	-	(0.03)	-	(0.02)
OVER_62	-	-	-0.104	-	-0.109
	-	-	(0.14)	-	(0.12)
ρ_0	-	-	-	-0.465	-0.349
	-	-	-	(0.21)**	(0.25)

Table 3. Regression Results. Female Sample (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5
Panel D: Ordered Probit Coefficient Estimates. Regime 1					
CON	-	0.298	0.217	0.302	0.263
	-	(0.30)	(0.28)	(0.40)	(0.37)
AGE10	-	0.885	0.859	0.903	0.903
	-	(0.10)**	(0.10)**	(0.13)**	(0.12)**
AGESQ10	-	-0.099	-0.094	-0.102	-0.100
	-	(0.01)**	(0.01)**	(0.01)**	(0.01)**
MARRY	-	-0.121	-0.112	-0.193	-0.158
	-	(0.06)*	(0.06)*	(0.09)**	(0.08)**
INC	-	0.000	0.005	-0.015	-0.008
	-	(0.04)	(0.03)	(0.05)	(0.04)
INCSQR	-	-0.004	-0.004	-0.003	-0.004
	-	(0.00)	(0.00)*	0.00	(0.00)
EDU	-	-0.032	-0.034	-0.043	-0.042
	-	(0.01)**	(0.01)**	(0.01)**	(0.01)**
OWN	-	-0.048	-0.044	-0.059	-0.060
	-	(0.06)	(0.05)	(0.07)	(0.07)
EXERCISE	-	-0.268	-0.262	-0.282	-0.272
	-	(0.07)**	(0.06)**	(0.08)**	(0.08)**
VIGOROUS	-	-0.012	-0.009	-0.017	-0.013
	-	(0.01)	(0.01)	(0.01)*	(0.01)
μ	-	1.094	-	1.097	-
	-	(0.10)**	-	(0.15)**	-
Panel E: Boundary Parameters. Regime 1					
θ	-	-	0.035	-	0.080
	-	-	(0.10)	-	(0.14)
W_FREQ	-	-	0.017	-	0.016
	-	-	(0.01)*	-	(0.01)
OVER_62	-	-	0.081	-	0.093
	-	-	(0.09)	-	(0.12)
ρ_1	-	-	-	0.5413	0.462
	-	-	-	(0.18)**	(0.21)**
Sample Size	15259	15259	15259	15259	15259
Max-L	15813.252	15583.575	15581.189	15588.680	15585.783

Notes:

Standard errors in parenthesis. Significance: **: 1%; *: 5%

Model 1: Ordered Probit

Model 2: Latent Class Ordered Probit

Model 3: Latent Class Generalized Ordered Probit

Model 4: Latent Class Correlated Ordered Probit

Model 5: Latent Class Correlated Generalized Ordered Probit

Table 4: Average Outcome Probabilities

	Normal Weight	Overweight	Obese
Male Sample			
All Classes	0.315	0.439	0.246
Class 0	0.312	0.399	0.046
Class 1	0.003	0.040	0.200
Female Sample			
All Classes	0.439	0.298	0.263
Class 0	0.412	0.198	0.069
Class 1	0.028	0.099	0.194

Note:
Average outcome probabilities presented for Model 5 only

Table 5: Total Marginal Effects

Variable	Normal Weight	Overweight	Obese	Normal	Overweight	Obese
		Male Sample			Female Sample	
W_FREQ	0.000	0.014	-0.014	0.000	0.002	-0.002
	(0.00)	(0.00)**	(0.00)**	(0.00)	(0.00)	(0.00)
OVER_62	0.000	0.026	-0.026	0.000	0.001	-0.001
	(0.00)	(0.01)**	(0.01)**	(0.00)	(0.01)	(0.01)
BORN_US	-0.095	-0.063	0.158	-0.146	0.041	0.105
	(0.01)**	(0.02)**	(0.02)**	(0.01)**	(0.01)**	(0.01)**
MF_OS	-0.008	-0.006	0.014	-0.066	0.019	0.048
	(0.01)	(0.01)	(0.02)	(0.03)**	(0.01)**	(0.02)**
WHITE	0.025	0.017	-0.042	0.099	-0.028	-0.071
	(0.01)**	(0.01)**	(0.01)**	(0.01)**	(0.01)**	(0.01)**
BLACK	0.011	0.007	-0.019	-0.074	0.021	0.053
	(0.01)	(0.01)	(0.02)	(0.02)**	(0.01)**	(0.01)**
COHORT1	-0.035	-0.023	0.058	-0.052	0.014	0.037
	(0.01)**	(0.01)**	(0.02)**	(0.02)**	(0.01)**	(0.01)**
COHORT2	-0.026	-0.017	0.044	-0.091	0.026	0.066
	(0.01)**	(0.01)**	(0.02)**	(0.03)**	(0.01)**	(0.02)**
AGE	-0.025	0.021	0.003	-0.027	0.022	0.005
	(0.00)**	(0.00)**	(0.00)	(0.01)**	(0.00)**	(0.00)
MARRY	-0.077	0.052	0.025	-0.029	0.035	-0.006
	(0.01)**	(0.01)**	(0.01)**	(0.01)**	(0.01)**	(0.01)
INC	-0.004	0.002	0.002	0.012	-0.001	-0.011
	(0.00)**	(0.00)	(0.00)	(0.00)**	(0.00)	(0.00)**
EDU	0.007	0.003	-0.010	0.015	-0.004	-0.011
	(0.00)**	(0.00)	(0.00)**	(0.00)**	(0.00)**	(0.00)**
OWN	-0.037	0.034	0.002	0.011	0.000	-0.011
	(0.01)**	(0.01)**	(0.01)	(0.01)	(0.01)	(0.01)
EXERCISE	-0.005	0.027	-0.021	0.020	0.019	-0.039
	(0.01)	(0.01)**	(0.01)**	(0.01)	(0.01)	(0.01)**
VIGOROUS	0.001	0.001	-0.002	0.016	-0.008	-0.008
	(0.00)	(0.00)	(0.00)**	(0.00)**	(0.00)**	(0.00)**

Table 6: Marginal Effects for Regime 0

Variable	**Normal Weight**	**Overweight**	**Obese**	**Normal**	**Overweight**	**Obese**
	Male Sample			Female Sample		
W_FREQ	0.000	0.016	-0.016	0.000	0.000	0.000
	(0.00)	(0.00)**	(0.00)**	(0.00)	(0.00)	(0.00)
OVER_62	0.000	0.032	-0.032	0.000	-0.013	0.013
	(0.00)	(0.01)**	(0.01)**	(0.00)	(0.02)	(0.02)
BORN_US	-0.096	-0.102	-0.005	-0.169	-0.049	-0.008
	(0.02)**	(0.02)**	(0.00)**	(0.02)**	(0.02)**	(0.01)
MF_OS	-0.009	-0.009	0.000	-0.077	-0.022	-0.004
	(0.02)	(0.01)	(0.00)	(0.03)**	(0.02)	(0.01)
WHITE	0.025	0.027	0.001	0.115	0.033	0.006
	(0.01)**	(0.01)**	(0.00)*	(0.02)**	(0.02)**	(0.01)
BLACK	0.011	0.012	0.001	-0.086	-0.025	-0.004
	(0.01)	(0.01)	(0.00)	(0.02)**	(0.01)*	(0.01)
COHORT1	-0.035	-0.037	-0.002	-0.060	-0.017	-0.003
	(0.01)**	(0.01)**	(0.00)**	(0.02)**	(0.01)*	(0.00)
COHORT2	-0.027	-0.028	-0.001	-0.106	-0.031	-0.005
	(0.01)*	0.01)	(0.00)**	(0.03)**	(0.01)**	(0.01)
AGE	-0.025	0.020	0.005	-0.029	0.017	0.012
	(0.00)**	(0.00)**	(0.00)**	(0.01)**	(0.00)**	(0.00)**
MARRY	-0.077	0.061	0.016	-0.036	0.021	0.015
	(0.01)**	(0.01)**	(0.00)**	(0.01)**	(0.01)**	(0.01)**
INC	-0.004	0.003	0.001	0.009	-0.006	-0.004
	(0.00)**	(0.00)**	(0.00)*	(0.00)**	(0.00)**	(0.00)**
EDU	0.007	-0.006	-0.001	0.013	-0.008	-0.005
	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**	(0.00)**
OWN	-0.037	0.029	0.008	0.009	-0.005	-0.004
	(0.01)**	(0.01)**	(0.00)*	(0.01)	(0.01)	(0.01)
EXERCISE	-0.006	0.005	0.001	0.008	-0.005	-0.003
	(0.01)	(0.01)	(0.00)	(0.02)	(0.01)	(0.01)
VIGOROUS	0.001	-0.001	0.000	0.015	-0.009	-0.006
	(0.00)	(0.00)	(0.00)	(0.00)**	(0.00)**	(0.00)**

Table 7: Marginal Effects for Regime 1

Variable	**Normal Weight**	**Overweight**	**Obese**	**Normal**	**Overweight**	**Obese**
		Male Sample			Female Sample	
W_FREQ	0.000	-0.002	0.002	0.000	0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)*	(0.00)*
OVER_62	0.000	-0.006	0.006	0.000	0.014	-0.014
	(0.00)	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)
BORN_US	0.001	0.039	0.163	0.024	0.090	0.113
	(0.00)	(0.02)**	(0.02)**	(0.01)*	(0.02)**	(0.01)**
MF_OS	0.000	0.003	0.014	0.011	0.041	0.052
	(0.00)	(0.01)	(0.03)	(0.01)	(0.02)**	(0.02)**
WHITE	0.000	-0.010	-0.043	-0.016	-0.061	-0.077
	(0.00)	(0.01)*	(0.02)**	(0.01)*	(0.02)**	(0.01)**
BLACK	0.000	-0.005	-0.019	0.012	0.046	0.058
	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)**	(0.01)**
COHORT1	0.000	0.014	0.059	0.008	0.032	0.040
	(0.00)	(0.01)**	(0.02)**	(0.00)*	(0.01)**	(0.01)**
COHORT2	0.000	0.011	0.045	0.015	0.057	0.071
	(0.00)	(0.01)*	(0.02)**	(0.01)**	(0.02)**	(0.02)**
AGE	0.000	0.002	-0.002	0.002	0.005	-0.007
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)*	(0.00)*
MARRY	0.000	-0.009	0.009	0.007	0.014	-0.021
	(0.00)	(0.00)*	(0.00)*	(0.00)	(0.01)**	(0.01)**
INC	0.000	-0.001	0.001	0.002	0.005	-0.007
	(0.00)	(0.00)	(0.00)	(0.00)*	(0.00)**	(0.00)**
EDU	0.000	0.009	-0.009	0.002	0.004	-0.005
	(0.00)	(0.01)*	(0.01)*	(0.00)**	(0.00)**	(0.00)**
OWN	0.000	0.005	-0.005	0.002	0.005	-0.008
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
EXERCISE	0.000	0.02	-0.022	0.011	0.024	-0.035
	(0.00)	(0.01)*	(0.01)*	(0.01)*	(0.01)**	(0.01)**
VIGOROUS	0.000	0.00	-0.001	0.001	0.001	-0.002
	(0.00)	(0.00)*	(0.00)*	(0.00)*	(0.00)	(0.00)