Do forests help to keep me fit?

Abstract

Increasing importance has been placed on understanding how the environment in which people live can help anti-obesity behaviour and policy. This tendency represents a shift away from a model characterised by individual responsibility in favour of one that focuses on so-called 'obesogenic environments'. Although an extensive body of literature stresses the importance of urban design in helping to eradicate obesity, there is, nevertheless, significant uncertainty in the science surrounding the relationship between body size and broad geographic areas. In this paper, we therefore widen the perspective from urban area planning to land planning. Specifically, we outline the incidence of forests helping to create an environment more favourable to outdoor physical activities, which at least improve health by lowering body mass index. The results demonstrate a relationship between forests and lower average body mass index (BMI); in other words, a reduction in the risk of being overweight. There is, however, no impact on obesity.

Keywords: Forest, Recreational activity, Obesogenic environments, Multilevel modelling

1. Introduction

Overweight and obesity are conditions where weight is greater than what is optimally considered healthy for a given height. These conditions are one of the most important health problems in the USA and Europe. According to the Global

Health Observatory (GHO) of the World Health Organization (WHO), 61.9% of American and 54.8% of European adults are overweight, of whom 23.5% and 20.4%, respectively, are obese. Overweight increases the likelihood of several diseases and the direct and indirect costs lie with government and household budgets. As an example, Finkelstein and Flebelkorn (2003) estimate average annual medical expenditures to be substantially higher for obese than for normal-weight individuals. In addition, Bhattacharya and Bundorf (2009) demonstrate that the obese have lower wages than the non-obese. Furthermore, Michaelowa and Dransfeld (2008) find that fiscal and regulatory measures to reduce obesity could help greenhouse emissions.

The emergence of obesity has become an increasing concern, including in middle income countries as a result of the quick shift in nutritional habits and sedentary working conditions (Popkin and Ng, 2007). The 'geography of obesity' exhibits an enormous variety of incidences of obesity around the world. However, as Etilé (2008) notes, geographic differences cannot be ascribed to differences in national eating patterns when within-country comparisons reveal different patterns between socio-demographic or socio-economic groups. In addition, different patterns emerge between regions of the same country (Ford et al., 2005; Holtgrave and Crosby, 2006; Mokdad et al., 2001, 2003).

Obesity is the outcome of long periods of imbalance between energy intake and energy expenditures during daily activities. Three causes of obesity arise from this definition: incorrect food choice, insufficient physical activity or both. Many authors stress the importance of socio-economic determinants of the pathological status, such as age (Chang et al., 2006; Miljkovic et al., 2008), gender (Miljkovic et al., 2008), race (Lakdawalla and Philipson, 2002), income (Drewnowski et al.,

2007) and occupational status (Drewnowski and Darmon, 2005; Loureiro and Nayga, 2005). Others emphasise how lifestyle and habits, an inclination for sport (Lakdawalla and Philipson, 2002), smoking (Huffman and Rizov, 2008) and educating oneself about nutritional facts (Loureiro et al., 2012) have a significant impact on daily physical activities, food choice behaviour and consequently, on individual weight.

According to Lakdawalla and Philipson (2002), one of the main reasons for increasing obesity among adults is the growing prevalence of sedentary jobs and leisure. Therefore, an emphasis on methods promoting physical activities emerges. Lake and Townshend (2006) define the 'obesogenic environment' as a model for understanding the external factors that may influence individual weight, which is to say the way in which the built environment provides the individual with opportunities or barriers to food intake and physical activity. Many researchers have concentrated their efforts on the influence of contextual factors on behaviour incentives for weight gain, such as sugar and fat prices (Miljkovic and Nganje, 2008), availability of food stores (Wang et al., 2006; White 2007) and urban planning (Frank et al., 2004; Lopez, 2004).

The aim of this paper is to understand, in the context of the obesogenic environment model, the positive impact of forests on the development of less obesogenic communities. A multilevel regression model has been applied for the purpose of combining the effects of individual factors (gender, age, education) and contextual determinants such as land use of population centres.

This paper is organised as follows: in section 2, a literature review of the influence of land use on weight and the importance of forest-centric recreational functions has been performed; in section 3, the empirical model and its data source

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are introduced; in section 4, results are provided; finally, section 5 is dedicated to conclusions.

2. Environment and weight

An extensive body of literature has established a relationship between urban features, land use and obesity. Frank et al. (2004) is one of the first works to emphasise the link between land use and BMI. The authors stress the association of high mix use areas (residential, commercial, office and institutional) with a lower probability for obesity as a consequence of an increasing willingness to engage in outdoor activities. In contrast, Lopez (2004), which focuses on urban planning, finds that urban sprawl increases obesity because of increased commuting time and the reliance on car and public transportation for daily transfers. Many other authors have found similar results (Smith et al. 2008; Rundle et al., 2007; Li et al. 2008; Wakefield, 2004).

In general, these papers stress the role that walkability of space in urban areas and neighbourhoods plays in encouraging outdoor activities for more than just recreational purposes. The presence of recreational activities in urban areas is often found to be positively associated with more physical activity and with healthier weights (Cohen et al., 2007; Fan and Jin, 2013; Giles-Corti et al., 2005). Yamada et al. (2012), starting from an extensive literature review on this issue, stress that the walkability of space is one of the key factors preventing obesity and encouraging healthy weight. In addition, they underscore the capacity of these results to be generalized for different geographic scales or for methods of measuring land use. The general conclusion of the literature is that a built environment offering more opportunities for outdoor activities reduces average weight and the willingness to

be overweight or obese.

One shortcoming of the previous studies is the limitation of the analysis to the opportunities an individual finds in neighbourhoods or urban areas. Farther afield, recreational opportunities are available in areas other than the proximity. From a broader geographic perspective, the forest offers a wide variety of energy intensive activities.

The primary function of forests has changed in recent years, transitioning away from economic functions such as timber production to more social and environmental dimensions. In terms of the latter aspects, much research has investigated and assessed the benefits of forests.

In general, natural resources are multifunctional, providing a wealth of goods and services of economic value. Many authors (Pearce, 2001; Zhongwei et al., 2001) identify five main benefits of forests: hydro-geological security and soil conservation, production of timber or other forest products (i.e., mushrooms, truffles, chestnuts), carbon sequestration and mitigation of climate change, naturalistic functions (biodiversity preservation) and tourist and recreational functions.

The present paper focuses on the touristic and recreational functions of forests that are directly involved with the quality of life of users. The recreational function is based on a wide range of energy intensive activities, including sports and hobbies such as hiking, bird watching, mountain biking, the collection of non-forest products (mushrooms, chestnuts, blueberries), hunting and so on.

An extensive body of literature has tried to estimate the recreational value of forest (see de Aragón et al., 2011; Voces Gonzàles et al., 2010; Wang, 2013) and formulate models for recreation demand (Smirnov and Egan, 2012). The previous papers underline the high value of the recreational function of forests, without

depending on intrinsic (spruce forest, oak forest, etc.) or extrinsic (type of soil, average temperature, etc.) characteristics of case studies; that is, many different types of forests are important for recreational purposes. Furthermore, many studies demonstrate the preference on the part of recreational users for certain forest attributes (Bestard and Font, 2009; Dhakal et al., 2012; Edwards et al., 2012; Horne et al., 2005; Koo et al., 2013; Nielsen et al., 2007), such as biodiversity, good mix of stand types, age and health of trees and landscape variety. As Termansen et al. (2013) noted, each of the following attributes are positively correlated with the extension of forests since large forest has a higher degree of animal and vegetable biodiversity, a greater mix of stand types, age and health of trees, a wider range of landscapes and greater recreational attractiveness. Particularly for recreational purposes, biophysical factors are crucial to determine the preferences of users (Edwards et al., 2012).

The hypothesis of this paper originates from two facts: *(i)* average individual weight is influenced by opportunities for outdoor activities afforded by land use, and *(ii)* forests provide a forum for energy intensive activities. Hence, does any relationship between individual weight and forests emerge?

In addition, analysing the connection between individual weight and forests helps provide a solution for the concerns of the previous literature. Plantinga and Bernell (2005) and Fan and Jin (2013) identify a potential weakness of causal relationships between obesity and the planning environment due to the possibilities of self-selection. In other words, more active individuals (from a physical point of view) may tend to live in areas that promote physical activities. Moreover, environment may force individuals to be more/less physically active than is normal. The hypothesis that residential location is chosen based on individual preferences

for recreational use of forests was tested and rejected by Abildtrup et al. (2013).

3. Empirical models

The dependent variable of the empirical models is the Body Mass Index (BMI) of adults, the most widely used measurement of human body shape, applied by both epidemiologists and scientists in population research. The BMI is calculated as height/weight^2 (in units kg/cm^2) and classifies people as overweight (BMI $\geq$ 25) or obese (BMI $\geq$ 30). Individual BMI has been associated with the amount of forest acreage in the region where an individual lives. The regions are the second NUTS administrative level of European Union (from here forward called regions).

To test the hypothesis, a simple two-level multilevel model is applied to estimate separately the individual determinants from the contextual determinants. Following Luke (2004) a general multilevel model can be written as:

$$
\begin{aligned}
\text{Level 1:} \quad & Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij} \\
\text{Level 2:} \quad & \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \\
& \beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j}
\end{aligned}
\tag{1}
$$

The system of equations of (1) defines the multilevel nature of the model. In the first (individual) level, BMI is a function of the average for each group (the intercept β_{0j}) and the individual determinants β_{1j}). The second level of the model indicates how individual parameters are functions of the second level predictors and variability. Thus, the average for each unit (the intercept β_{01}) is function of γ_{00} (the mean values of the first dependent variable) and the second level W_j covariate. The slopes of β_{1j} is a function of γ_{10} and γ_{11} which depend by W_j. In other words, the assumption of this model is the variables of the second level W_j

influence the average of each unit j of the first level and the predictors (β_{1j}) of first level.

The general hypothesis of this article postulates the influence of the extension of forests on average BMI, not, however, the influence of individual characteristics on BMI. Hence, the specification is what is often referred to as a random intercept-model, where the individual level of intercept is modelled using a regional predictor. The multilevel model applied is, at the first level:

$$
\begin{aligned}
\text{BMI}_{ij} =& \beta_{0j} + \beta_{1j}(\text{AGE}_{ij}) + \beta_{2j}(\text{GEND}_{ij}) + \beta_{3j}(\text{INT}_{ij}) \\
&+ \beta_{4j}(\text{EDU}_{ij}) + r_{ij}
\end{aligned}
\tag{2}
$$

and at the second level is

$$
\begin{aligned}
\beta_{0j} &= \gamma_{00} + \beta_{01}(\text{QBOS}_j) + u_{0j} \\
\beta_{1j} &= \gamma_{10} + u_{1j} \\
\beta_{2j} &= \gamma_{20} + u_{2j} \\
\beta_{3j} &= \gamma_{30} + u_{3j} \\
\beta_{4j} &= \gamma_{40} + u_{4j}
\end{aligned}
\tag{3}
$$

The mixed model is obtained by substituting (3) into (2)

$$
\begin{aligned}
\text{BMI}_{ij} =& \gamma_{00} + \gamma_{01}(\text{QBOS}_j) + \gamma_{10}(\text{AGE}_{ij}) + \gamma_{20}(\text{GEND}_{ij}) \\
&+ \gamma_{30}(\text{INT}_{ij}) + \gamma_{40}(\text{EDU}_{ij}) + u_{0j} + u_{1j}(\text{AGE}_{ij}) \\
&+ u_{2j}(\text{GEND}_{ij}) + u_{3j}(\text{INT}_{ij}) + u_{4j}(\text{EDU}_{ij}) + r_{ij}
\end{aligned}
\tag{4}
$$

The first level predictors are: age (AGE); a dummy variable equal to one if the individual is male (GEND); a dummy variable equal to one if the individual has

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at least a secondary education (EDU); an interaction variable of gender and age (INT = AGE*GEND). The interaction parameter is introduced due to the hypothesis that the effect of age differs between males and females. The second level predictor is the rate of regional land covered by forest (QBOS). A higher rate is the proxy of more opportunities for recreational activities as aforementioned (Termansen, 2013). In addition, the regional land covered by forest is a proxy of availability rather than accessibility. This aspect is crucial since as noted by Cho et al. (2014), distance has a less negative impact to decrease demand for non-static activities

Other factors, that influence the BMI and are stressed in the literature, such as race or food habits, are not included in the analysis because they are homogeneously distributed across Italian regions. As regards income status, the effects are captured by education, since these two variables are strongly correlated in Italy as demonstrated by Fiaschi and Gabbriellini (2013). Other contextual factors such as beaches or mountains are considered endogenous to the model.

In addition, a two-level non-linear model with a logit link function is estimated with the same covariate of (2) to determine whether forest density influences the probability of being overweight or obese. The first level model is:

$$
\text{Prob}(Y_{kij} = 1 | \beta_j) = \Phi_{ij}; \qquad \log[\Phi_{ij}] = \eta_{ij}
$$
$$
\eta_{ij} = \beta_{0j} + \beta_{1j}(\text{AGE}_{ij}) + \beta_{2j}(\text{GEND}_{ij}) + \beta_{3j}(\text{INT}_{ij}) + \beta_{4j}(\text{EDU}_{ij})
$$
(5)

The second level model is the same as (2). Thus, combining (2) with (5) the mixed model is:

$$\begin{aligned}
\eta_{ij} = & \gamma_{00} + \gamma_{01}(\text{QBOS}_j) + \gamma_{10}(\text{AGE}_{ij}) + \gamma_{20}(\text{GEND}_{ij}) \\
& + \gamma_{30}(\text{INT}_{ij}) + \gamma_{40}(\text{EDU}_{ij}) + u_{0j} + u_{1j}(\text{AGE}_{ij}) \\
& + u_{2j}(\text{GEND}_{ij}) + u_{3j}(\text{INT}_{ij}) + u_{4j}(\text{EDU}_{ij})
\end{aligned} \tag{6}$$

When $k = 1$, Y_{ij} is a dummy variable equal 1 when an individual is over-weight; when $k = 2$ the Y_{ij} is a dummy variable equal 1 when an individual is obese.

4. Data

The data set used to obtain individual characteristics is taken from Italy World Health Survey 2003, a sample survey conducted by the WHO (WHO, 2014). This survey provides information about individual characteristics related to region of residence. Data for forest surface is taken from Corine Land Cover project 2006 of the European Environment Agency (EEA). Tables 1 and 2 present summary statistics of the variables included in the analysis of 913 individuals in 18 Italian regions. In this survey, data for Valle d'Aosta and Molise was not collected because of the small population of the two regions.

The average BMI varies among Italian regions, between 22.8 in Umbria to 26.6 in Basilicata. In general, South Italy has an average BMI higher than in the North. Among northern Italian regions, Veneto has the highest average BMI with 25, while Tuscany has the highest BMI of the central regions.

Figure 1 displays the distribution of forests in Italy. On the national level, forests cover approximately 41% of the total area of the peninsula. Trentino-South Tyrol has the greatest distribution of forest (88% of regional surface), followed by Liguria (76% of forest land use of total regional area) and Piedmont (56% of

forest) in North-West Italy. The smallest area is located in Apulia, in South-East Italy, where only 11% of the total regional area is covered by forest.

As already stated, the recreational function of forests is based on a variety of activities including hiking, bird watching, mountain biking, collection of non-forest products and hunting. In general these activities are equally distributed in all regions in Italy. However, there are some peculiar cases due to specific local forest characteristics. As an example, in the North of Italy the main recreational activity is hiking through the mountain ranges, principally the Alps and the Dolomites (Tempesta and Marangon, 2004, Thiene and Scarpa, 2008). In the central area and South of the peninsula many people use forest for hunting (Marinelli et al., 1990; Tirendi 2003), for the collection of non-forest products, and for tourism purposes (Riccioli et al., 2012; Brunori et al., 2006).

5. Results and discussion of empirical model

To test the significance of regional effects, a two-way ANOVA is applied to BMI, with regions, gender and education as treatments. The results in Table 3 displays a significant effect on BMI of residence in different regions. Although gender and education are significant, as interaction terms, the two are not significant, implying no region by gender interaction and no region by education interaction. Therefore, both the individual and context have an impact on BMI, but each affects BMI independently.

A likelihood ratio (LR) test is conducted to compare the null multilevel model with a null single-level model; the goal is to understand if a multilevel model fits better than a single level model. The LR test shows a chi2(1) = 9.11; Prob > chi2 = 0.0025. Thus, there is overwhelming evidence of regional effects on BMI.

After testing for regional effects, it is useful to calculate the intraclass correlation coefficient (ICC). The ICC is equal to 2.2%. That is, a portion of the total variability in BMI is caused by variations between regions, although a large part derives from variations between individuals. The results of empirical models are shown in Table 4.

The method by which the prevailing literature identified the individual determinants is significant and has an important impact. Males are more likely to have a higher BMI than females, while young people have a lower BMI than do older. The interaction effects between age and gender are small but significant, with a negative sign. That is, aging males tend to experience an increase in BMI at a slower rate than do females. Education has a fundamental relationship in determining BMI. According to empirical models, more educated people have, ceteris paribus, a BMI that is 1.10 less than others. The rate of regional forests is significant and has a positive impact on reducing average weight. A single percentage point of additional forested regional territory decreases the average BMI by 0.0187.

Table 5 exhibits the random effects on the slope of the first level determinants. As expected, the second level effects are not significant; thus, the slope of first level covariates does not vary in each region. In other words, the context of environment does not influence the relationship between personal characteristics and BMI but does have a direct impact on individuals.

The Table 6 shows the results of a two-level non-linear binary model. The land covered by forests is significant and has a positive impact in reducing the probability of being overweight. The estimated parameter for regional land covered by forest equals -1.48 and indicates that, holding all other variables constant (includ-

ing random effects), within a region the odds that an individual is overweight are 0.86 times the odds in cases where land covered is 10 percentage points greater. Alternatively, for a given region, all other effects held constant, the odds of an individual being overweight are 1/0.86=1.16 times the odds for cases where land covered by forests is 10 percentage points smaller. In other words, higher forest extension is associated with lowered chances of an individual being overweight.

Thanks to the estimate coefficients shown in Table 6, it is possible to draw a prediction graph according to the extension of forests. Figure 2 exhibits the probabilities of being overweight for a 40-year-old male or female with a secondary education. This figure underscores the relationship between overweight and extension of forests. The probability of being overweight decreases sharply in regions with a higher rate of land covered by forests.

The model for obesity does not exhibit a significant coefficient for forests. For this pathological status, the environment determinants are not important. The cause of obesity may often be linked to genetic factors or illness, this may be why availability of forest has no impact on this condition. Alternatively, on a smaller geographical scale, context factors could have an impact on obesity, but with this model it is impossible to say.

6. Conclusions

Overweight and obesity are global epidemics (Caballero, 2007) which call for a multidimensional strategy to curb them. Promoting outdoor activities is one of the elements of this strategy, but it is necessary to analyse all elements that provide incentives to an active lifestyle and energy intensive leisure. The results demonstrate a relationship between average BMI and the extension of forests. However,

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the magnitude of the effect does not affect the magnitude of individual factors. Environment plays a key role in determining average BMI and controlling overweight. At the same time, individual characteristics are crucial when attention is shifted to obesity. In other words, the planning of the environment has an important role as a preventative step, but when the issue of overweight becomes one of obesity, policy should be directed towards other approaches.

The existing literature stresses the importance of land use as a key factor in the promotion of physical activity; however, it concentrates on smaller geographic context, usually urban. These results are robust because the self-selection bias noted by Fan and Jin (2013) is less pronounced, by virtue of the fact that individuals who follow more active lifestyles do not live exclusively in regions with higher recreational opportunities.

These results have a twofold implication. First, forests improve health not only in terms of clean air and water but also in terms of reducing overweight. Second, the protection and promotion of the extension of forests should be regarded as an additional alternative to existing health policy options.

Although the burden of determining BMI in terms of forest extension is not crucial, the implications for policy could be attractive. Health impacts of increased public intervention to protect forests and encourage their expansion can be increased by expansion of the user basin. The cost of such improvements could be compensated, at least partially, by the reduction of direct and indirect costs of overweight, as estimated by several authors (Finkelstein and Flebelkorn, 2003; Bhattacharya and Bundorf, 2009; Michaelowa and Dransfeld, 2008).

The mechanism that links the extension of forests and BMI should be the same as the one detailed in the literature stressing the capacity of urban environments to

enhance participation in outdoor physical activities. Indeed, the recreational function of forests is well-known, and many studies have emphasized the high value of forests and parks in terms of the willingness of the public to pay for recreational use. The combination of these two facts should explain the relationship between forests and BMI. However, in the obesogenic environment model, mechanisms apart from the provision of incentives could link BMI and forests. For example, living in a 'greener' region could reduce stress and provide clean air and water, which help people to be healthier or at least more active. Separate analyses of these effects would require a higher qualification of forests to determine the degree of accessibility, usability, distance from urban centres and number of areas equipped for non-static activities. Unfortunately, at the national level, information collected using standardized methods is not always available.

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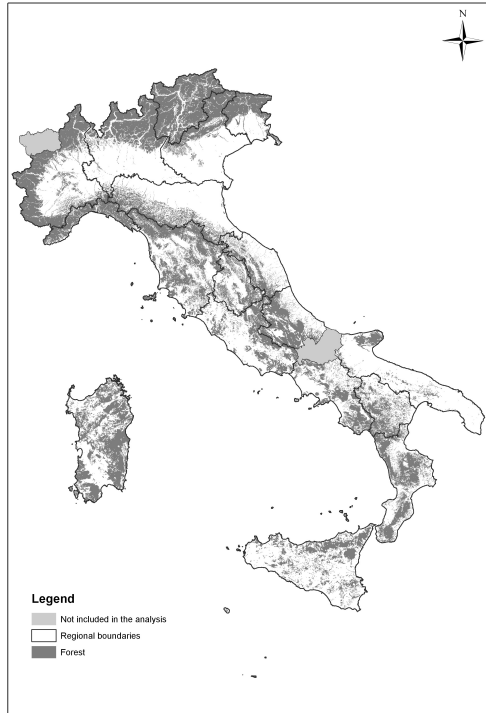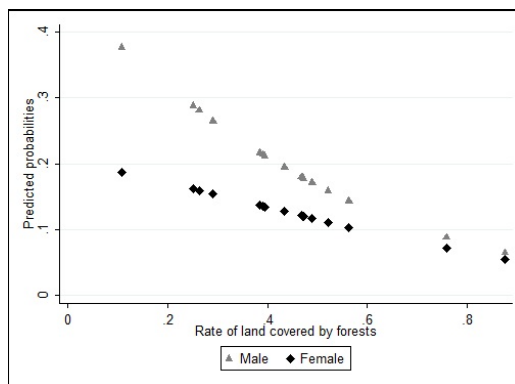
Figure 1: The distribution of forests in Italy

Figure 2: The predicted probabilities for being overweight for a 40-year-old person

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Table 1: Descriptive statistics: continuous variable

Variables	Mean	Standard deviation	Median	Interquartile range
Age	48.19	18.06	46	29
BMI	24.60	3.83	24.22	5.16
Rate of land covered by forests	0.40	0.16	0.39	0.21

Table 2: Descriptive statistics: categorical variables

Variables	(%)
Overweight people	
Not overweight	60.13
Overweight	39.87
Obese people	
Not obese	91.68
Obese	8.32
Gender	
Male	56.63
Female	43.37
Education	
Less than primary school	5.37
Primary school completed	15.12
Secondary school completed	26.83
High school (or equivalent) completed	40.42
College / pre-university / university completed	11.94
Post graduate degree completed	0.33

Table 3: The two-way ANOVA

Source	Partial SS	df	MS	F	Prob>F
Model	2043.94	53	38.56	2.91	0.0001
Region	373.08	17	21.95	1.66	0.0452
Gender	110.62	1	110.62	8.36	0.0039
Education	414.57	1	414.57	31.32	0.0001
Region*education	164.05	17	9.65	0.73	0.7745
Region*gender	246.66	17	14.51	1.1	0.3521
Residual	11368.88	859	13.23		
Total	13412.83	912	14.71		

Table 4: Results: estimation of fixed effects

Covariates	Coefficient[a,b]	Standard error	t-ratio	p-value
Intercept (γ_{00})	21.92	0.77	28.13	<0.001
Rate of regional land covered by forest (γ_{01})	-1.87	0.87	-2.13	0.048
Age (γ_{10})	0.07	0.01	6.20	<0.001
Gender (γ_{20})	3.20	0.70	4.52	<0.001
Age*Gender (γ_{30})	-0.03	0.01	-2.46	0.024
Education (γ_{40})	-1.10	0.27	-3.94	<0.001

[a] The estimation method is the Restricted Maximum Likelihood. The Maximum Likelihood produces biased estimators when there are few second level groups (Snijders and Bosker, 1999).

[b] The general assumption of the same variance of the residual errors in all groups is tested computing the one-way analysis of variance of the groups on the absolute value of the residuals (Hox, 2002). Results are F=1.11 with 17 degree of freedom; Prob>F is 0.3382.

Table 5: Estimation of variance components

Random Effect	Standard Deviation	Variance Component	p-value
Intercept (u_0)	1.69	2.85	0.066
Age (u_1)	0.03	0.0007	0.088
Gender (u_2)	0.78	0.60	>0.500
Age*Gender (u_3)	0.02	0.00025	>0.500
Education (u_4)	0.43	0.19	>0.500
level-1, r	3.44	11.85	

Table 6: Results of two-level non-linear binary model

Parameter[a,b]	Overweight				Obesity			
	Coefficient	Odds Ratio	t-ratio	p-value	Coefficient	Odds Ratio	t-ratio	p-value
Intercept (γ_{00})	-1.48	0.23	-4.97	<0.001	-3.49	0.03	-3.36	0.004
Rate of regional land covered by forest (γ_{01})	-1.41	0.24	-3.67	0.002	-1.40	0.25	-1.63	0.122
Age (γ_{10})	0.03	1.03	6.40	<0.001	0.03	1.03	2.14	0.047
Gender (γ_{20})	1.31	3.71	2.48	0.024	0.59	1.81	0.57	0.575
Age*Gender (γ_{30})	-0.01	0.99	-1.18	0.254	-0.004	0.99	-0.25	0.809
Education (γ_{40})	-0.49	0.61	-2.74	0.01	-0.87	0.42	-2.55	0.021

[a] The estimation method is the Penalized Quasi-Likelihood (PQL) estimation procedure.

[b] The random effects are omitted since all coefficients are not significant for both models.