

Does size matter? A propensity score approach to the effect of BMI on labour market outcomes

Silvia Conduto de Sousa *

(Draft - please do not quote.)

Abstract

It is unquestionable the public health dimension the phenomenon of obesity has taken both in the United States and more recently in Europe. Health economists have dealt with overweight and obesity prevalence estimating their direct and indirect costs. In this paper, the effect of overweight and obesity is analyzed in terms of labour market outcomes. Using the ECHP, this paper provides a new approach both in terms of scope of analysis, since it focus on European countries, and in terms of methodology, since it proposes an alternative technique so far not applied to this particular problem. Recognizing the endogeneity associated in the relation between body mass measures and labour market outcomes, this paper uses a matching approach, overcoming the difficulty in finding suitable instruments associated with an instrumental variable approach. Average treatment effects on the treated are estimated. Parametric results point to the importance of overweight and obesity on labour market outcomes. Results obtained from matching corroborate parametric results concerning the effect of BMI on labour force participation. Female labour force participation, as well as employment, is negatively affected by a BMI indicating overweight while male labour force participation and employment react positively to a BMI indicating overweight; and this gender pattern can be observed for Northern and Southern European countries.

Keywords:obesity; labor market outcomes; propensity score and matching.

JEL classification: *J16; J21; J71; C21*

*Department of Economics of the University of Minho. Email: ssousa@eeg.uminho.pt. The author thanks the participants at the ESPE conference in Paris for their comments. Part of this research took place while the author was concluding her PhD at the European University Institute. Financial support from the European University Institute, Italy; the University of Minho and the Ministry of Foreign Affairs, Portugal is therefore gratefully acknowledged.

Contents

1	Introduction	1
2	Obesity prevalence in Europe: an increasing trend	2
3	Obesity and wages	3
3.1	Cawley's model of weight and wages	3
3.2	Dealing with endogenous BMI	4
4	Propensity score matching	6
4.1	The potential-outcome approach	6
4.2	The main assumptions for matching	7
4.3	The average effect of overweight on overweighed individuals (ATT)	8
5	Data: European Community Household Panel	9
6	Does size matter?	10
6.1	What can be learnt from parametric estimates?	10
6.2	The effect of weight on labour market outcomes	10
7	Final remarks	11
8	References	12
9	Appendices	13

1 Introduction

Developed societies have devoting an increasing attention to the prevalence of obesity among the younger population. Initially identified as a problem of mainly adult population, obesity has become a phenomenon affecting not only adults but also teenagers and children. The concern has reached the mass media and today, more and more frequently, we are being confronted with the issue. Presented as a public health problem its causes and consequences have been analyzed within the economics discipline mainly within a framework of cost analysis suggested by health economists.

Economists and other health professionals refer to overweight as an excess of body weight compared to set standards and obesity as having an abnormally high proportion of body fat. Generally, the body mass index (BMI) is used to measure both overweight and obesity. The BMI is a direct calculation based on height and weight, and it is not gender specific. Although BMI does not directly measure the percentage of body fat, it provides a more accurate measure of overweight and obesity than relying on weight alone. Computed as the ratio of an individual's weight (measured in kilograms) and his height (measured in meters) squared, the National Institutes of Health in the United States identify overweight with a BMI between 25 and 29.9 Kg/m^2 , and obesity with a BMI of 30 Kg/m^2 or above. This definition is consistent with the recommendations of the World Health Organization and that used most of developed countries.

Health economists, mainly interested in the economic costs associated with overweight and obesity, have identified and attempted to measure two types of costs: direct and indirect costs. Direct costs include health care cost related to preventive diagnostic and treatment services (for example, physician visits, medications and hospital and nursing care). Indirect costs are related to the value of wages lost by people unable to work because of the illness or disability, as well as the future earnings lost by premature death. While there has been a spur of literature dealing with identifying and measuring direct costs,¹ economists have not been as successful concerning the measurement of indirect costs. Moreover, the attention overweight and obesity prevalence have captured has not been even across continents. While in the United States its has been thoroughly studied, studies focussing on Europe are scarce and very limited.

This particular paper attempts to shed some light over the costs of obesity in

¹See Pereira *et al* (1999) for references.

Europe, proposing an alternative analysis of its indirect costs, namely its costs in terms of labour market literature concerning the United States (for example: Averett and Korenman, 1996; Cawley, 2004; and Pagan and Davila, 1997) which argues that there is a negative correlation between body weight and wages among females.

According to Cawley's recent results (Cawley, 2004), there are three broad explanations for such phenomenon: obesity lower wages either by reducing productivity or simply due to discrimination; low wages cause obesity as low income people choices of food are more limited and may be reduced to more fattening products; and the possibility that unobserved variables cause both obesity and low wages. As in Cawley's study, this paper analyzes how obesity relates to wages in Europe and how this relation varies across countries and individuals with different characteristics.

The remainder of the paper is organized as follows. Section II, presents overweight and obesity trends across Europe. Section III briefly summarizes Cawley's approach, its advantages and disadvantages for our purpose. Section IV proposes an alternative approach based on the potential outcome and elaborates the matching strategy for the binary and multi-valued treatment cases. Section V presents the data, section VI results and section VII concludes.

2 Obesity prevalence in Europe: an increasing trend

According to the International Obesity Task Force (IOTF,2004) the prevalence of obesity in the majority of European countries has increased by about 10% to 40%, in the last 10 years. This increasing trend is relatively common among women, particularly in Southern and Eastern European countries, while in Scandinavian countries it seems to be levelling off. Current prevalence data from individual countries suggests that the prevalence of obesity ranges from 10% to 20% for men and 10% to 25% for women. According to this organization, "the current situation concerning obesity reflects the profound changes in societies over the past 20-30 years that have created an environment that promotes a sedentary lifestyle and the consumption of a high fat, energy dense diet" (IOTF, 2004).

The prevalence among children is also rising significantly. The major increases in adult obesity levels are now mirrored in rapidly rising levels among children. Children are more likely to become overweighted with greater risk of cardiovascular disease, diabetes and other disorders.(IOTF and EASO, 2002).

When data is presented geographically, two trends stand out: the first is the generally lower levels of overweight found among children in Central and Eastern European countries whose economies have gone through periods of different levels of recession during their period of economic and political transition in the 1990s; the second is the prevalence of overweight to be higher in Southern European countries, particularly the Mediterranean countries which show prevalence rates for overweighted children in the range of 20-40%, while those in Northern areas show rates in the range 10-20% (Lobstein and Frelut, 2003).

3 Obesity and wages

3.1 Cawley's model of weight and wages

2

Individual's wages are related to BMI and other variables (X is a vector of variables that affect wages), at time t , according to equation:

$$\ln W_{it} = \beta BMI_{it} + \phi X_{it} + \epsilon_{it} \quad (1)$$

where ϵ is the residual.

Exogeneity of BMI assures that OLS estimates of β can be interpreted as a consistent estimate of the true effect of BMI on wages. However, there are several reasons to believe that BMI is endogenous such as the fact that BMI is influenced by non genetic factors like individual choices and environment and the possibility that obesity may be influenced by wages. Endogeneity of BMI instead leads to inconsistent estimates of the effect of weight on wages. In an attempt to identify the possible sources of endogeneity, the residual in (1) is decomposed into a genetic component, a non genetic component and a residual v , i.i.d. over individuals and time.

$$\epsilon_{it} = G_{it} + NG_{it} + v_{it} \quad (2)$$

The possibility of reverse causality, on the other hand, is expressed in the following equation:

$$BMI_{it} = \gamma X_{it} + \alpha W_{it} + \eta Y_{it} + g_{it} + ng_{it} + \lambda_{it} \quad (3)$$

²(Cawley, 2004)

In (3), X is the same vector of variables affecting wages, W wages and Y a vector of variables affecting BMI but not wages directly, g and ng are the influence of genetics and non genetics on BMI, respectively, and λ represents the residual.

Together, these equations show the potential problems in estimating β : current wages may affect BMI; genetic factors affecting BMI are likely to be correlated to genetic factors affecting wages, and the same is valid for non genetic factors, implying a violation of the assumption that BMI is uncorrelated with ϵ in equation (1) and therefore leading to biased estimates of β .

3.2 Dealing with endogenous BMI

Previous literature had already identified the endogeneity problem and had proposed some possible solutions to overcome such problem and produce consistent unbiased estimates of the effect of weight on wages. Cawley (2004, p.453-4) has identified three different strategies, which, in fact can be reduced to two: an instrumental variable (IV) strategy based on the existence of a variable or vector of variables, highly correlated with BMI but not correlated with the residual ϵ and a differencing strategy based on the existence of another individual with similar genes.

Cawley (2004), has considered a third strategy based upon the use of lagged values of BMI, which implicitly assumes that these would not be correlated with current wage residual. In this paper, we consider that this procedure is equivalent to an IV strategy which uses lagged values of BMI as instruments. This strategy, however, would not solve the problem raised by the fact that genetic and non genetic factors influencing wages and BMI may be correlated. Using this strategy in the previous research³ it has been found that lower income or wages were associated with being overweight in the past, for young females. No or little evidence was found for males.

In our case, however, this particular approach cannot be applied. Lagged values of BMI referred to seven years earlier and the series of reported data on BMI available for Europe are much shorter. Moreover, it implied following the same individual along the time period available and that would lead to significant losses of information.

Cawley's IV strategy is based on finding a variable or vector of variables Z (which could be lagged values of the contaminated variable), strongly correlated

³Gortmalet *et al* (1993); Sargent and Blanchflower (1995); and Averett and Korenman (1996), all cited in Cawley (2004)

with BMI but not correlated with the residual in equation (1), that could be used as an instrument for BMI. Pagan and Davila (1997), after failing to reject the hypothesis that weight was uncorrelated with the error term of the wage equation, have used family poverty level, health limitations, and indicators about self-esteem as instruments and have failed to reject the hypothesis that IV estimates were different from OLS estimates which stated that overweighted females earned less than their more slender counterparts. This result was attributed to the quality of the instruments which were also likely to be correlated with the error term in the wage equation.

The second differencing strategy based on the existence of another individual with highly correlated genes (either a same-sex sibling or a twin), assumed that all unobserved heterogeneity was constant within pairs so that all relevant unobserved heterogeneity was differenced away and that wages did not influence weight. This strategy has been applied by Averett and Korenman (1996), Behrman and Rosenzweig (2001)⁴ and, more recently, by Conley and Galuber (2005). Its main flaw is the limited dimension of the sample available for European countries, and this is the main reason for not following a similar strategy in this paper. Behrman and Rosezweig (2001)⁵, after applying a differencing strategy, have used an IV strategy to remove any remaining endogeneity, using lagged values of weight as an instrument. However, their IV estimate is not statistically significant.

Cawley (2004) follows the first type of approach, arguing that the use of a larger data set (a pooled sample of 13 years of the National Longitudinal Survey of Youth - NLSY for the United States of America) and better instruments (the BMI of a sibling, controlling for the age and gender of the sibling) allow for the production of more precise and consistent estimates. Moreover, he accounts for reporting errors for self-reported height and weight, based on additional information from the Third National Health and Nutrition Examination Survey. He finds that weight lowers wages, for white females, while negative correlations between weight and wages observed for other gender-ethnic groups seem accounted by unobserved heterogeneity.

In this paper, the scope to correct for reporting errors is rather limited due to the lack of more precise information (for example, information based on physical examinations). Moreover, it is quite unusual to have such long series (13 years) for even reported data on BMI. In our case, we can only count with three to four years of data. As noted before, the use of instruments based on family relations,

⁴Cited in Cawley (2004)

⁵Cited in Cawley (2004)

more specifically, on siblings or twins, has led to rather small samples. This sample limitation has been suggested to be the source of less precise and consistent results.

In this paper, an alternative strategy based on propensity score methods is proposed. The main idea is to overcome the problem of finding a suitable instrument among the information available in the data set used, without the trade-off of losing too much information.

4 Propensity score matching

Proposed initially in the evaluation literature, propensity score matching allows for correcting the estimation of the treatment effects controlling for the existence of confounding factors that may be in the origin of biased estimates. Confounding factors instead may result from the fact that assignment into treatment and control groups is not random.

In this section we briefly present the potential-outcome approach in the origin of the matching approach presented later.

4.1 The potential-outcome approach

Let the binary variable B_i indicate the treatment status "being overweight or not" ($B_i \in 0, 1$), $L_i(1)$ the potential labour market outcome of individual i under the treatment state "being overweight" ($B_i=1$), and $L_i(0)$ the potential labour market outcome of individual i under the treatment state "not being overweight" ($B_i = 0$). The observed labour market outcome for individual i is given by $L_i = B_i L_i(1) - (1 - B_i) L_i(0)$. The individual treatment effect is given by $\beta_i = L_i(1) - L_i(0)$, but can not be computed because only $L_i(1)$ or $L_i(0)$ is observed. So, the objective will be to estimate the average effect of treatment on the treated individuals (ATT):

$$\hat{\beta}_{|B_i=1} = E(\beta_i | B_i = 1) = E[L_i(1) | B_i = 1] - E[L_i(0) | B_i = 1] \quad (4)$$

According to the previous equation the labour market outcome of an individual overweighted is compared to the labour market outcome of the same individual not overweighted. In other words, the labour market outcome of an individual overweighted is compared to what would have been his labour market outcome were he not overweighted. The first expected value $E[L_i(1) | B_i = 1]$ can be identified in the subsample of the treatment group. The second expected value, the counterfactual expectation $E[L_i(0) | B_i = 1]$ requires further assumptions in order to be identifiable. Observing the non overweighted individuals provides information on

the counterfactual outcome of the treated in the non treatment status. The replacement of $E[L_i(0)|B_i = 1]$ with $E[L_i(0)|B_i = 0]$ may not be the right strategy since treated and untreated individuals may differ in their characteristics determining the outcome if they themselves select into treatment. Random assignment into treatment would ensure that potential outcomes would be independent of treatment status and treatment effect could consistently be estimated by the difference between the observed means of the outcome variable in the treatment group and in the non treatment group. However, random assignment situations are rare. In the case under analysis, being overweighed is not likely to be random since it may depend on some observed characteristics which may also influence labour market outcomes. For example, highly educated individuals may be more concerned with their appearance and their physical condition and, at the same time, are likely to have more positive labour market outcome. In such cases, appropriate identifying assumptions are used to devise alternative estimators and matching methods to construct a suitable comparison group.

4.2 The main assumptions for matching

The main issue concerning matching is pairing together treatment and untreated units that are similar in terms of their observable characteristics. When the main differences between treatment and untreated groups can be captured in the observable, pre-treatment, covariates, matching methods can produce unbiased estimates of the treatment effect.

Implicitly to matching is the assumption⁶ that conditional to pre-treatment covariates, outcomes are independent of assignment to treatment. The matching procedure is then based on the stratification of the sample of treated and untreated with respect to covariates X_i that determine the selection into treatment and the outcome of interest. Selection bias is eliminated as long as after stratification all X_i variables are observed and balanced between treated and untreated groups. Within each stratum is like having a separate small randomized experiment and differences between treated and untreated outcomes provide unbiased estimates of the treatment effect.

This assumption is denominated unconfoundedness or conditional independence assumption⁷ and implies that, within each stratum or cell defined by the covariates

⁶Additionally to the assumption of stable unit-treatment values - SUTVA. The SUTVA assumption means that the labour market outcome of an individual is only dependent on the BMI of the individual and not on the BMI of any other individual in the population.

⁷See Becker and Ichino (2002) and Vuri (2003) for details. See Ichino *et al* (2005) for a discussion and suggestions on testing.

X , treatment is random and that the selection into treatment depends upon the observables X_i up to a random component. Formally: $L_i(0) \perp B_i | X_i$, meaning that the outcomes of the non-treated are independent of the participation into treatment B_i , as long as one controls for the observables X_i . In these conditions, there is no selection on unobservables: if two individuals identical in terms of their observable characteristics are found, then it is likely that they will also be alike in terms of their unobservable characteristics. Being these correlated, controlling for observables implies also controlling for the unobservables. Additionally, it assumes that the $\Pr(B_i = 0 | X_i = x) > 0$, for all x , which means that matching will only be done over the common support region of X_i , where the treated and the non-treated groups overlap. It follows that⁸:

$$E(L_i(0) | X_i, B_i = 1) = E(L_i(0) | X_i, B_i = 0) \quad (5)$$

which allows to use the matched non-treated individual to measure how the treated labour market outcome would have been, on average, had they not have been treated.

4.3 The average effect of overweight on overweighed individuals (ATT)

In order to estimate the ATT, firstly the differences between the outcomes of the two groups are computed conditional on the observables and then averaged over the distribution of observables in the treated population, $X_i | B_i = 1$. Formally, it is given by:

$$\begin{aligned} \hat{\beta}_{|B_i=1} &\equiv E[L_i(1) | B_i = 1] - E[L_i(0) | B_i = 1] = \\ &E_X \{ [E[L_i(1) | X_i, B_i = 1] - E[L_i(0) | X_i, B_i = 1]] | B_i = 1 \} = \\ &E_X \{ [E[L_i(1) | X_i, B_i = 1] - E[L_i(0) | X_i, B_i = 0]] | B_i = 1 \} = \\ &E_X \{ [E[L_i | X_i, B_i = 1] - E[L_i | X_i, B_i = 0]] | B_i = 1 \} \end{aligned}$$

The difficulty in reconciling a finite sample conditioned on X_i and a high dimension vector of observables led to the proposal of an alternative form of stratifying the sample using of the conditional probability to participate into treatment $p(X_i) \equiv \Pr(B_i = 1 | X_i = x) = E(B_i | X_i)$ denoted propensity score.⁹ Satisfaction of the balancing property ensures that the treated and the non-treated with the same value of the propensity score will have the same distribution over the vector of the observables X_i . Formally, the balancing property is given by: $X_i \perp B_i | p(X_i)$. Moreover, if the conditional independence assumption is satisfied, it can be shown

⁸See Rosenbaum and Rubin (1983)

⁹Rubin (1977) and Rosebaum and Rubin (1983)

that $L_i(0) \perp B_i | p(X_i)$ also holds. Therefore, $p(X_i)$ can constitute the basis for the matching, reducing the multidimensional problem to one dimension. The propensity score is the probability of participating in a particular stratum where the decision to participate or not is random.

Unbiased estimates of the ATT are given by the difference between treatment and non treatment average outcomes at any value of $p(X_i)$:

$$\hat{\beta}_{|B_i=1} \equiv E_{p(X)} \{ [E[L_i | B_i = 1, p(X_i)] - E[L_i | B_i = 0, p(X_i)]] | B_i = 1 \}$$

Initially, the propensity score has to be estimate and only then the ATT.¹⁰ Problems in obtaining exact matches tend to arise when continuous variables are considered. In such cases, some margin between treated and untreated individuals has to be allowed.

Any standard probability model can be used to estimate the propensity score: $Pr(B_i = 1 | X_i) = F[h(X_i)]$, com $F[.]$ the normal or the logistic cumulative distribution and $h(X_i)$ a function of covariates with linear or higher order terms. In this paper, the propensity score is estimated using a probit model, using the algorithm in Becker and Ichino (2002). Concerning the estimation of ATT, results using nearest-neighbour matching and radius matching are reported.¹¹

5 Data: European Community Household Panel

The empirical analysis of the effect of weight on wages in Europe is based on data from the European Community Household Panel (ECHP), promoted and developed by the Eurostat. The ECHP supplies a longitudinal panel of private households and individuals across the European Union countries over eight consecutive years. For the purpose of this paper, the last three waves, corresponding to years 1999, 2000 and 2001 are used since there is only data concerning weight, height and BMI from 1998 onwards; and nine countries will be considered.¹²

Given the purpose of the analysis, i.e., effects on labour market outcomes, working age individuals were selected. Three labour market outcomes can be analyzed: being active or not; being employed or not; and wage variation. In the first two cases, the dependent variable is an indicator variable for labour market status (taking value one if individual is active/working and value zero otherwise). In the last case, the dependent variable is the log of wages. This paper will focus on the first

¹⁰See Dehejia and Wahba (1998).

¹¹See, for example, Becker and Ichino (2002) and Vuri (2003) for details.

¹²Several countries, which already carried out national surveys, have abandoned the ECHP questionnaire in 1997: Germany, Luxembourg and the UK. Moreover, for some countries there is no information on height, weight or BMI (the Netherlands and France) or for current wages (Sweden)

two cases. Analogously, body weight was also considered in several forms: indicator variables for the clinical classifications (underweight; overweight and obese); an indicator for being overweighed; an indicator for being obese; and the BMI of each individual. Additionally, a set of regressors was considered in order to control for personal characteristics: gender; age; marital status; presence and number of children in the household; for differences in human capital: education level; for employment characteristics: years of actual work experience; indicator variables for type of occupation (white or blue collar); an indicators for part-time work and public sector employment; and, finally, an indicator for health satisfaction.

Table 1 presents descriptive statistics for the sample of females and table 2 for the sample of males.

6 Does size matter?

6.1 What can be learnt from parametric estimates?

Parametric estimates of the effect of BMI on labour force participation are reported in tables 3 (for females) and 4 (for males). Although, not controlling for endogeneity, the results obtained are quite interesting in the sense that being overweighed is not an handicap to participate in the labour market in the case of males whereas in the case of females being overweighed is negatively correlated to labour force participation. Moreover, it is interesting to note that a positive general feeling about own health is positively correlated with participating in the labour market. Recall, however, that these results require great caution in deriving any conclusion on the impact of overweight on labour market participation since, as argued before, there might be an endogeneity problem which has not been taken cared of, yet.

6.2 The effect of weight on labour market outcomes

In the presence of endogenous body mass measures, parametric techniques which do not account for endogeneity, will produce bias estimates. Therefore, alternative approaches have been adopted in the literature, ranging from fixed parametric techniques using lagged weight, fixed effects and random effects models (when there is a panel dimension to be explored) and instrumental variables. In this paper, matching techniques based on propensity scores are used. Preliminary results corroborate parametric results in the sense that being overweighed has a negative effect on female participation (and employment) while a positive effect is found for men. Tables 5 and 6 report ATT results for the effect of overweight on labour force participation.

Overweight effects on labour force participation were also estimated for a subsample of Northern countries and a subsample of Southern countries. In line with the full sample results, being overweighed has a negative effect in terms of female labour force participation and a positive effect in terms of male labour force participation. Concerning women, the effect is more marked in Southern European countries implying that overweight is more penalizing for Southern European women. In the case of men, the effect is sensitive to the method applied leading to contradictory conclusions concerning North-South effects. Tables ?? and ?? report the results. Overweight effects on the employment were also estimated for subsamples of Southern and Northern countries.¹³ Tables 7 and 8 report results for females and males. The effect of overweight on labour force participation is generally milder than on employment in the case of females and generally stronger in the case of males. The strength of the effect is sensitive to the matching method applied. Still, the direction of the effect (negative for females and positive for males) is quite robust.

7 Final remarks

It is an unquestionable fact that overweight and obesity prevalence has become a problem of the industrial world. The direct costs that have been estimated are relevant and the indirect costs, although their estimation poses greater difficulty, also point to the need for an active response to the problem. In this paper, the interest was on labour market outcomes and to what extent being overweighed or obese had an impact on labour force participation and employment. Recognizing the endogeneity problem associated to the measure of overweight or obesity, is proposes an alternative approach to an instrumental variable procedure, which allows to analyze the phenomenon in some European countries. Propensity scores based on the observables were estimated and matching techniques applied to correct for the biased estimates when using parametric methods. Parametric results were nevertheless presented as a benchmark for comparison. According to these results, there is a positive influence of weight on labour force participation in the case of males and an opposite influence in the case of females. Results from estimating average treatment effects on the treated corroborate this relation between BMI and labour market outcomes. However, in what concerns the effect on labour force participation, the size of the effect varies: in the case of females, the ATT estimates are greater than OLS estimates and generally greater than probit estimates; in the

¹³Due to computer limitations, results for the whole sample are not, yet, available.

case of males, ATT estimates are generally greater than OLS estimates and smaller than probit estimates.

Finally, it should be noted that this relation can be analysed from different perspectives: labour force participation; employment; wages and even occupational distributions. So far, these have only been partially covered. The way weight is taken into account may also vary. Either indicator variables for being above predefined thresholds ($BMI > 25$ or $BMI > 30$) or the continuous variable BMI can be used providing different analytical dimensions of the same phenomenon. Again, not all dimensions have been explored.

8 References

Averett, S. and S. Korenman (1996), "The economic reality of the beauty myth", *Journal of Human Resources*, 31, 2, 304-330.

Becker, S. O. and A. Ichino (2002), "Estimation of average treatment effects based on propensity scores", *The Stata Journal*, 2, 4, 331-350.

Cawley, J. (2004), "The impact of obesity on wages", *Journal of Human Resources*, 39, 2, 451-476.

Conley, D. and R. Glauber (2005), "Gender, body mass and economic status", *NBER Working Paper Series*, 11343.

Dehejiba, R. and S. Wahba (1998), "Propensity Score Matching Methods for Non Experimental Causal Studies", *NBER Working Paper*, n. 6829.

European Commission (2001), "European Community Household Panel - UDB Description of Variables", *Eurostat Doc. Pan*, n. 166.

Ichino, A., F. Mealli and T. Nannicini (2005), "Sensitivity of matching estimators to unconfoundedness - an application to the effect of temporary work on future employment", *mimeo*.

International Obesity Task Force (2004), "The global epidemic of obesity", in <http://www.obesity.chair.ulaval.ca/iotf.htm>.

International Obesity Task Force and European Association for the Study of Obesity (2002), "Obesity in Europe: The case for action", *International Association for the Study of Obesity Report*.

Lobstein, T. and M. L. Frelut (2003), "Prevalence of overweight among children in Europe", *Obesity Reviews*, 4, 195-200.

Pagan, J. A. and A. Davila (1997), "Obesity, Occupational attainment and Earnings", *Social Science Quarterly*, 8, 3, 756-770.

Pereira, J., C. Mateus and M. J. Amaral (1999), "Custos da obesidade em Portugal", *APES Working Paper*, n. 4.

Rosenbaum, P. R. and D. B. Rubin (1983), "The central role of the propensity score in observational studies for causal effects", *Biometrika*, 70, 41-55.

Rubin, D. B. (1979), "Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observation Studies", *Journal of the American Statistical Association*, 74, 318-328.

Vuri, D. (2003), "Propensity Score Estimates of the Effects of Fertility on Marital Dissolution", *European University Institut Working Paper*, ECO n. 4.

9 Appendices

Table 1: Descriptive statistics, females

	N	Mean	SD	Min.	Max.
lfp	82505	.5773347	.4939861	0	1
employ	82505	.5096055	.4999108	0	1
bmi	82505	23.91049	4.220301	6.377551	84
bmi25	82505	.3225623	.4674596	0	1
bmi30	82505	.0846009	.2782886	0	1
age	82505	38.45448	13.01111	16	62
married	82505	.6133325	.4869893	0	1
child12	82505	.3050482	.4604306	0	1
nchild14	82505	.5298346	.8577481	0	9
education	82505	.53924	.4984609	0	1
ywexp	82505	3.773662	6.592592	0	22
north	82505	.1451427	.3522468	0	1
south	82505	.6401067	.4799718	0	1
whitecollar	41063	.7756861	.4171347	0	1
publicwork	82505	.3275317	.4693158	0	1
fulltimework	82505	.4366402	.4959723	0	1
satisfaction	82505	.941143	.2353584	0	1

Where bmi is the BMI; bmi25 and bmi30 are indicator variables which take value 1 when individual's BMI is equal or greater than 25 or 30, respectively, and 0 otherwise; age is the age of the individual; married is an indicator variable that takes value 1 if the individual is married and 0 otherwise; child12 is an indicator variable that takes the value 1 if there are children aged 12 or below in the household of the individual and 0 otherwise; nchild14 is the number of children ages 14 or below in the household; education is an indicator variable that takes value 1 if the individual has completed the secondary school or more and 0 otherwise; ywexp is the individual work experience measured in years; north and south are indicator variables that take value 1 if the individual's country is in Southern Europe (Portugal, Spain, Italy or Greece) or in Northern Europe (Denmark or Finland), respectively, and 0 otherwise; publicwork is an indicator variable that takes value 1 if the individual works in the public sector and 0 otherwise; fulltimework is an indicator variable that takes value 1 if the individual works full time and 0 otherwise and, finally, satisfaction is an indicator variable that takes value 1 if the individual has a positive opinion about his/her health status and 0 otherwise.

Table 2: Descriptive statistics, males

	N	Mean	SD	Min.	Max.
lfp	80162	.8194032	.3846862	0	1
employ	80162	.7575659	.4285581	0	1
bmi	80162	25.39736	3.658476	3.8739	119.4444
bmi25	80162	.4939498	.4999665	0	1
bmi30	80162	.0949577	.2931583	0	1
age	80162	38.13771	12.946	1	62
married	80162	.5775679	.4939497	0	1
child12	80162	.2964996	.4567167	0	1
nchild14	80162	.5169656	.8539031	0	9
education	80162	.5379232	.4985629	0	1
ywexp	80162	6.704311	7.939579	0	22
north	80162	.1473516	.3544583	0	1
south	80162	.6408024	.4797682	0	1
whitecollar	57397	.7044968	.4562726	0	1
publicwork	80162	.5796263	.493622	0	1
fulltimework	80162	.7336768	.442038	0	1
satisfaction	80162	.9437015	.2304987	0	1

Where bmi is the BMI; bmi25 and bmi30 are indicator variables which take value 1 when individual's BMI is equal or greater than 25 or 30, respectively, and 0 otherwise; age is the age of the individual; married is an indicator variable that takes value 1 if the individual is married and 0 otherwise; child12 is an indicator variable that takes the value 1 if there are children aged 12 or below in the household of the individual and 0 otherwise; nchild14 is the number of children ages 14 or below in the household; education is an indicator variable that takes value 1 if the individual has completed the secondary school or more and 0 otherwise; ywexp is the individual work experience measured in years; north and south are indicator variables that take value 1 if the individual's country is in Southern Europe (Portugal, Spain, Italy or Greece) or in Northern Europe (Denmark or Finland), respectively, and 0 otherwise; publicwork is an indicator variable that takes value 1 if the individual works in the public sector and 0 otherwise; fulltimework is an indicator variable that takes value 1 if the individual works full time and 0 otherwise and, finally, satisfaction is an indicator variable that takes value 1 if the individual has a positive opinion about his/her health status and 0 otherwise.

Table 3: Parametric estimates of the effect of BMI on labour force participation - females

	OLS (1)	Probit (2)
bmi25	-.009 (.004)***	-.04 (.01)***
age	.08 (.0009)***	.24 (.003)***
age2	0 (.0000112)***	-.002 (.0000344)***
married	-.1 (.004)***	-.31 (.01)***
child12	-.05 (.004)***	-.16 (.01)***
education	.17 (.003)***	.48 (.01)***
satisfaction	.14 (.007)***	.41 (.02)***
Const.	-1.03 (.02)***	-4.38 (.05)***
Obs.	82505	82505

Where bmi is the BMI; bmi25 is an indicator variable which takes value 1 when individual's BMI is equal or greater than 25 and 0 otherwise; age is the age of the individual; age2 is the square of the age of the individual; married is an indicator variable that takes value 1 if the individual is married and 0 otherwise; child12 is an indicator variable that takes the value 1 if there are children aged 12 or below in the household of the individual and 0 otherwise; education is an indicator variable that takes value 1 if the individual has completed the secondary school or more and 0 otherwise; and, finally, satisfaction is an indicator variable that takes value 1 if the individual has a positive opinion about his/her health status and 0 otherwise.

Table 4: Parametric estimates of the effect of BMI on labour force participation - males

	OLS (1)	Probit (2)
bmi25	.02 (.002)***	.1 (.01)***
age	.09 (.0007)***	.37 (.003)***
age2	0 (8.08e-06)***	-.004 (.0000422)***
married	.06 (.003)***	.5 (.02)***
child12	-.007 (.003)***	.11 (.02)***
education	-.008 (.002)***	-.06 (.01)***
satisfaction	.26 (.005)***	1.01 (.02)***
Const.	-1.09 (.01)***	-6.44 (.06)***
Obs.	80162	80162

Where bmi is the BMI; bmi25 is an indicator variable which takes value 1 when individual's BMI is equal or greater than 25 and 0 otherwise; age is the age of the individual; age2 is the square of the age of the individual; married is an indicator variable that takes value 1 if the individual is married and 0 otherwise; child12 is an indicator variable that takes the value 1 if there are children aged 12 or below in the household of the individual and 0 otherwise; education is an indicator variable that takes value 1 if the individual has completed the secondary school or more and 0 otherwise; and, finally, satisfaction is an indicator variable that takes value 1 if the individual has a positive opinion about his/her health status and 0 otherwise.

Table 5: Propensity score estimates of the effect of BMI on labour force participation, females

	ATT	SE
Nearest-neighbour	-0.018	0.004
Radius $r = 0.01$	-0.053	0.004
Radius $r = 0.0001$	-0.050	0.004

Propensity score estimated using a Probit model with specification: $P(BMI25_i = 1) = F(\text{age interval; marital status; presence of children aged below 12; education level; satisfaction concerning health status})$. SE: analytical standard errors.

Table 6: Propensity score estimates of the effect of BMI on labour force participation, males

	ATT	SE
Nearest-neighbour	0.016	0.003
Radius $r = 0.01$	0.045	0.003
Radius $r = 0.0001$	0.044	0.003

Propensity score estimated using a Probit model with specification: $P(BMI25_i = 1) = F(\text{age interval; marital status; presence of children aged below 12; education level; satisfaction concerning health status})$. SE: analytical standard errors.

Table 7: Propensity score estimates of the effect of BMI on labour force participation, females

	North		South	
	ATT	SE	ATT	SE
Nearest-neighbour	-0.012	0.009	-0.027	0.005
Radius $r = 0.01$	-0.030	0.009	-0.047	0.005
Radius $r = 0.0001$	-0.037	0.009	-0.037	0.005

Propensity score estimated using a Probit model with specification: $P(BMI25_i = 1) = F(\text{age interval; marital status; presence of children aged below 12; education level; satisfaction concerning health status})$. SE: analytical standard errors.

Table 8: Propensity score estimates of the effect of BMI on labour force participation, males

	North		South	
	ATT	SE	ATT	SE
Nearest-neighbour	0.023	0.008	0.012	0.005
Radius $r = 0.01$	0.015	0.008	0.050	0.005
Radius $r = 0.0001$	0.012	0.008	0.049	0.005

Propensity score estimated using a Probit model with specification: $P(BMI25_i = 1) = F(\text{age interval; marital status; presence of children aged below 12; education level; satisfaction concerning health status})$. SE: analytical standard errors.

Table 9: Propensity score estimates of the effect of BMI on employment, females

	North		South	
	ATT	SE	ATT	SE
Nearest-neighbour	-0.032	0.009	-0.032	0.005
Radius $r = 0.01$	-0.060	0.015	-0.045	0.005*
Radius $r = 0.0001$	-0.069	0.008	-0.039	0.005*

Propensity score estimated using a Probit model with specification: $P(BMI25_i = 1) = F(\text{age interval; marital status; presence of children aged below 12; education level; satisfaction concerning health status})$. SE: bootstrapping standard errors; * analytical standard errors.

Table 10: Propensity score estimates of the effect of BMI on employment, males

	North		South	
	ATT	SE	ATT	SE
Nearest-neighbour	0.029	0.007	0.022	0.004
Radius $r = 0.01$	0.013	0.025	0.074	0.004*
Radius $r = 0.0001$	0.006	0.008	0.075	0.004*

Propensity score estimated using a Probit model with specification: $P(BMI25_i = 1) = F(\text{age interval; marital status; presence of children aged below 12; education level; satisfaction concerning health status})$. SE: bootstrapping standard errors; * analytical standard errors.