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Are employers discriminating with respect to weight? European Evidence using Quantile Regression

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ABSTRACT

The aim of this research is to investigate the relationship between obesity and wages, using data for nine countries from the European Community Household Panel (ECHP) over the period 1998–2001. We improve upon the existing literature by adopting a Quantile Regression approach to characterize the heterogenous impact of obesity at different points of the wage distribution. Our results show that (i) the evidence obtained from mean regression and pooled analysis hides a significant amount of heterogeneity as the relationship between obesity and wages differs across countries and wages quantiles and (ii) cultural, environmental or institutional settings do not seem to be able to explain differences among countries, leaving room for a pure discriminatory effect hypothesis.

1. Introduction

Although the obesity phenomenon is more recent in Europe compared to the US, it does create equal concern given that its prevalence has increased by 10–40% in most European countries over the last decade (WHO, 2003) and obesity levels based on measured data already range from 13% to 23% (WHO, 2006). Even more worrisome is the spreading of obesity among teenagers and children (WHO, 2006). Apart from being a debilitating condition, obesity is also related to numerous health problems and many chronic diseases. In addition, obesity is not only a health but also an economic phenomenon (Finkelstein et al., 2005).

The aim of this paper is to focus on the economic side of this phenomenon by examining the relationship between obesity and wages in a cross-national perspective for Europe. So far, the literature on the relationship between weight and wages has focused on two main research topics: on one side the socioeconomic determinants of overweight and obesity,[1] on the other side the costs associated with obesity. With respect to this last point, economists have identified two types of costs: direct

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[1] See Philipson and Posner (1999), Lakdawalla and Philipson (2002), Cutler et al. (2003), Chou et al. (2002) for the US, Loureiro and Nayga (2005) for OECD countries, and Sanz de Galdeano (2005) for European countries.

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and indirect costs. Generally speaking, direct costs include health care costs related to diagnostic and treatment services, while indirect costs are related to the value of wages lost due to inability to work because of illness, as well as earnings lost due to discrimination. This last aspect is the focus of our paper.

Starting with the pioneering work by Register and Williams (1990) several researchers have studied the existing relationship between excess weight and labor market outcomes.[2] The vast majority of empirical evidence produced by those studies agrees with the view that, at individual level, obesity and labor outcomes (wage, occupation and labor force participation) are negatively related, although this relationship may vary across population groups. If this is due to a pure, a priori, discrimination of obese workers or it is, instead, the result of some economic relationship is still a matter of debate. Fall in productivity levels (Cawley, 2000; Pagan and Davila, 1997), reduced training opportunities caused by physical difficulties (Baum and Ford, 2004) and additional costs of the health insurance covered by the employers and charged on wages (Bhattacharya and Bundorf, 2005) are among the main reasons used to explain such a negative correlation.

Although using individual data, all the evidence collected by this literature is based on a mean regression approach. This represents a major shortcoming as researchers are not allowed to investigate the role of obesity at different points of the wage distribution, and the observed average effect may, indeed, hide more complex behaviors. In fact, it could be that obesity affects individual wage differently at the bottom or at the top of the wage distribution.[3] For example, obesity could represent a serious problem in all those contexts where a high level of interaction with the public is required or where an intense physical activity is necessary. On the contrary, it may not represent a serious problem at high level of wages or, equivalently, in all those cases where intellectual activity is needed. Alternatively, as suggested by Hamermesh and Biddle (1994), appearance may count more than responsibility and managerial skills (although mainly for women) at the top of the wage distribution. Therefore, by adopting a mean regression approach we could miss relevant pieces of information on individual heterogeneity that may be extremely useful for a correct understanding of the phenomenon and for tailoring effective anti-discrimination policies.

The aim of this research is to improve upon the existing literature on two main aspects. First, we adopt a quantile regression approach, to investigate if and at what level of wages obesity represents a problem. Second, our analysis is based on data from nine countries included in the European Community Household Panel (ECHP), but differently from most work on this topic we capture country heterogeneity by modeling the relationship between obesity and wages country by country. Our results show that the evidence obtained from mean regression and pooled analysis hides some heterogeneity as the relationship between obesity and wages differs across wage quantiles and countries. Further, there is no evidence that the results obtained can be related to existing differences in cultural, environmental or institutional settings across countries. Finally, it is important to highlight that the majority of evidence collected so far must be interpreted as statistical association rather than as causal effect. Nevertheless, in the last part of the paper, we try to assess the causal effect by adopting an instrumental variable strategy in the context of quantile regression.

The paper proceeds as follows. Section 2 discusses the theoretical framework and presents an overview of the literature on the relationship between excess weight and the labor market outcome. Section 3 illustrates the data used and reports the main descriptive statistics. Section 4 introduces the empirical strategy adopted and reports the econometric results. In Section 5 we deal with the problem of endogeneity between wages and obesity and present some results based on Instrumental Variable Quantile Regression (IVQR) technique. Finally, Section 6 draws some conclusions.

2. Empirical relationship between obesity and wages: background and literature review

Following Register and Williams (1990), Loh (1993) and Gortmaker et al. (1993) the relationship between wages and weight has been usually modelled by means of the traditional human capital wage equation:

$$W_{i,t} = \beta_0 + \beta_1 \mathrm{BMI}_{i,t} + \varphi X_{i,t} + \varepsilon_{i,t}, \quad \text{for} \quad i = 1, \ldots, N; \ t = 1, \ldots, T. \tag{1}$$

where the subscript i refers to individual, t is time, BMI is the body mass index, defined as individual weight (measured in kilograms) divided by the square of height (measured in metres),[4] $X_{i,t}$ is a $[NT \times K]$ matrix of time-varying explanatory variables, ε is the vector of residuals.

Based on Eq. (1) and using different data sets and estimation techniques, studies on the US data find mixed results on the relationship between wages and obesity. In particular, Gortmaker et al. (1993) find a negative relationship between wages and obesity but no evidence to support the hypothesis that obesity differentials are confounded by health status, since controlling for health status limitation does not change their results. Moreover, they reject the hypothesis that socioeconomic origin or ability account for the obesity differential. Averett and Korenman (1996) find that obese women have lower family income with respect to non-obese women and that differences in economic status by BMI increase when they use a lagged weight value or restrict the sample to women who were single or childless when the weight was reported.

[2] See among others Averett and Korenman (1996), Pagan and Davila (1997), Cawley (2000, 2004), Bhattacharya and Bundorf (2005), Brunello and d'Hombres (2007), Sousa (2005), and Garcia and Quintana-Domeque (2006, 2007).

[3] Similar concerns have been raised by Fahr (2006) who finds evidence that the body mass–wage relation is non-linear.

[4] Although the vast majority of researches on obesity are based on BMI measures, the medical literature agrees that they are seriously flawed because they do not distinguish fat from fat-free mass such as muscle and bone. For an updated analysis of these issues see Burkhauser and Cawley (2008).

Pagan and Davila (1997) find that women pay a penalty for being obese due to labor market discrimination, while overweight males sort themselves into jobs, via occupational mobility, to offset this penalty.[5] Conley and Glauber (2007) find that obesity is associated with a reduction in women's wage and income by 18% and 25%, respectively, and a reduction in women's probability of marriage by 16%. These effects persist across the life course, affecting older women as well as younger women. Baum and Ford (2004) find that both men and women experience a persistent wage penalty over the first two decades of their career. Cawley (2000, 2004) finds that weight lowers wages for white women and that in absolute value this reduction is equivalent to the wage effect of one year of education, two years of job tenure and three years of work experience. Behrman and Rosenzweig (2001) show that the significant negative relationship between adult BMI and wages found in cross-sectional estimates reflects only a correlation between unmeasured earning endowment and BMI, and it disappears when controlling for endowments common to monozygotic twins. Cawley and Danziger (2005) examine the relationship between weight and labor market outcome in a sample of current and former welfare recipients. They show that after controlling for individual fixed effects the estimates of the correlation of obesity and different labor market outcomes is not longer significant.

Similarly, in the European context, there are country specific studies for England, Scotland, and Wales (Sargent and Blanchflower, 1994), England (Morris, 2006, 2007), Germany (Cawley et al., 2005) and Denmark (Greve, 2007). Sargent and Blanchflower (1994) find no relationship between earning and obesity for men and a statistically significant inverse relationship between obesity and earnings for women. Morris (2006) shows that BMI has a positive and significant effect on occupational attainment for males and a negative and significant effect for females. For Germany, Cawley et al. (2005) find that obesity is negatively associated with wages, both for men and women, when using OLS technique. However, once they control for endogeneity using genetic factors, they conclude that there is no significant relationship between weight and wages. For Denmark, Greve (2007) finds a negative and significant relationship between BMI and the probability to be employed for women and a not insignificant relationship for men.

European wide analyses have been conducted using pooled data from the European Community Household Panel (ECHP) by Sousa (2005), Brunello and d'Hombres (2007), Lundborg et al. (2007) and Sanz de Galdeano (2007). Country-by-country European analysis has, instead, been done by Fahr (2006) and Garcia and Quintana-Domeque (2006, 2007). Sousa (2005) focuses on the impact of the BMI on labor force participation. She finds that being overweight decreases labor force participation for women, but it increases labor force participation for men. However, she is not able to estimate the obesity effect for each country separately, because using the propensity score matching approach reduces enormously the sample size. Brunello and d'Hombres (2007) find a negative and statistically significant impact of obesity on wages independently of gender for the pooled sample of countries. Furthermore, the negative relationship between obesity and wage is higher in Southern Europe than in Northern Europe and the size of the effect of the BMI on wage depends on whether an individual lives in an area with higher or lower than area's average BMI, suggesting that local economic and social environment does matter. Lundborg et al. (2007) analyze the effect of obesity on employment, hours worked and hourly wages in 10 European countries for people aged 50 and above. Pooling all the countries, they find that obesity is negatively associated with being employed for both men and women and with female hourly wages. Moreover, when grouping the countries in Nordic, Central and Southern, they find that the effects of obesity on labor market outcomes differ across Europe. Sanz de Galdeano (2007) focuses on the costs of obesity in terms of health, use of health care services and absenteeism. She finds that obesity is negatively associated with health, especially for women and in Northern and Central European countries. Moreover, obesity is shown to be positively associated with the demand for general practitioner and specialist services. Concerning the relationship between obesity and absenteeism, obese women in some countries are found to be absent from work more often than healthy-weight women, while no significant effect is found for men.

A main drawback of these studies is that they rely on a common effect of obesity on wages across the whole Europe or country groups. As shown by Fahr (2006) and Garcia and Quintana-Domeque (2006, 2007), allowing for country-by-country analysis provides more insights into the relationship between wages and obesity. Fahr (2006) analyzes wage penalties associates with deviation from a social norm on BMI. He estimates an equation where log of wages is regressed on two dummies capturing the influence of a deviation from the social norm, and on two dummies that account for the influence of deviations from an optimal BMI from a medical point of view. He finds that deviations of more than three index points in body mass in the upward direction from the norm is sanctioned with about 7% decrease in hourly wages in Austria, Greece and Spain. Garcia and Quintana-Domeque (2007) show that there is weak evidence that obese workers are more likely to be unemployed or tend to be more segregated in self-employment jobs than their non-obese counterparts. Moreover, they find that the relationship between labor market outcomes and obesity is heterogeneous across countries and gender and it can be explained by the role of some labor market institutions, such as collective bargaining and employer-provided health insurance.

Overall, two main lessons can be learned from this literature review: (i) the evidence gathered on the relationship between wages and obesity is far from being conclusive; (ii) country heterogeneity plays an important role and further analysis at country level or even at sub-region level should be undertaken whenever data are available. At the same time, a major criticism to be raised is that all these findings are based on ''mean'' values over the wage distribution. As also Garcia and Quintana-Domeque (2007) have pointed out, average effect may, indeed, hide more complex behaviors. Therefore, it is crucial to investigate the role of obesity at different points of the wage distribution, as it could be that

[5] In this last case, male overweight workers choose jobs where they find a productivity advantage over the non-obese or where they have a premium for undertaking more employment related risks.

obesity is related to individual wage differently at the bottom or at the top of the wage distribution. In what follows, we fill this gap by exploring the relationship between obesity and wages across countries and over the wage distribution through quantile regression.

3. Data and descriptive statistics

Our empirical analysis is based on data from the European Community Household Panel (ECHP), a dataset designed and coordinated by Eurostat, the European Statistical Office. The ECHP supplies a longitudinal panel of private households and individuals across countries of the European Union over eight consecutive years, from 1994 to 2001, with a focus on household income, living conditions, individual health, education and employment status. Moreover, the harmonized design of the ECHP ensures a good level of comparison across countries and over time.[6] We only consider those countries (Denmark, Belgium, Ireland, Italy, Greece, Spain, Portugal, Austria and Finland) and years (1998–2001) where information on weight and height is available. As done in previous studies, we drop potential outliers by restricting the sample to include only individuals with BMI above 15 and below 50. Moreover, we exclude pregnant women, and we further restrict our analysis to full-time dependent employees aged between 25 and 64 years.[7,8]

The dependent variable in our analysis is the log hourly wage for the respondent's current job. In order to make data from different countries comparable, we converted nominal wage into real wage using the time-varying purchasing power parity conversion index provided by the ECHP. Log wage is then regressed on a set of covariates such as a measure of obesity along with a group of control variables like age, education, training, household compositions, health status (bad or good health status), number of days absent from work, smoking habits, private or public sector of activity, occupation and sector of activity, insurance paid by the employer, time and country dummies as control variables. These control covariates are widely used in wage models in order to control for systematic differences in observed characteristics between individuals, as some of them may affect simultaneously weight and wages and their effects need to be netted out.[9] Concerning our measure of obesity, it is important to note that the standard specification in this literature has been to assume a linear relationship between the treatment and the outcome (see for example Brunello and d'Hombres, 2007), and the parameter associated with this variable defines the effect of interest. However, as noted more recently by some researchers (Kline and Tobias, in press; Shimokawa, 2008) this linearity assumption is not always credible. In fact, as also Kline and Tobias (in press) states, it may happen that wages respond less to changes in the BMI for "underweight" or "normal" compared to "overweight" or "obese" individuals. In alternative, it can happen that underweight and overweight individuals experience similar wage penalties generating an inverted U-shaped relationship between BMI and log wages. In all these situations standard linear treatment-response models are unable to capture these more complex relationships. There are several ways to account for non-linearities in the relationship between wages and BMI. Parametrically this can be done by including high order polinomials of the variable of interest or by using categories ("obese" vs. "non-obese" or finer categories such as "underweight", "normal", "overweight" and "obese"). An alternative is to adopt a non-parametric or semiparametric approach as recently done by Kline and Tobias (in press) and Shimokawa (2008).

In our specific case the assumption of linearity has been rejected through a series of formal and informal tests. In particular, (i) we run a RESET test that rejected the hypothesis of linearity of the continuous BMI variable and (ii) a graph from an unconditional kernel regression that clearly shows how health care costs at individual level (proxied by the number of visits to a GP) exhibit a discontinuity when the BMI is around 30 kg/m^2, for both males and females.[10] Based on this evidence, our strategy is then to use a parametric approach with the BMI categorized in four dummies (standard clinical classifications of BMI are *underweight* (BMI below 18.5), *normal* (BMI between 18.5 and 25), *overweight* (BMI between 25 and 30), and *obese* (BMI above 30)) with the normal weight as reference category. Table 1 provides summary statistics of the individual BMI categories, by country and sex. Men are more likely to be overweight and obese than women: 44.7% and 9.9% are, respectively, overweight and obese, compared to 22.4% and 7.1% for women. The prevalence of overweight and obesity varies also across countries. The table also shows that about 10% of women in both Denmark and Finland are obese, compared to 3.3% in Italy. Similar differences across countries exist also for men; in Spain the obesity rate is 12.8%, close to that in Belgium and Finland (11% and 11.8%, respectively), and far from Italy's rate (7.1%). Tables A.2 and A.3 in Appendix A report the full set of summary statistics for the pooled sample and by country.

[6] For further details on the ECHP, see Peracchi (2002).

[7] As noted by a referee, this age group may appear too broad as some individuals may not be affected by wage penalties as they get close to the retirement age. Individuals between 25 and 54 years of age should have higher perspectives in terms of career and wage opportunities (or penalties), and for this reason could represent a more appropriate group for our analysis. However, empirical results do not change significatively across the two age group selections. For this reason we'd rather prefer to use the larger age group, given that by reducing the sample we may incur in sample size problems, even more severe when estimating quantile model at country level.

[8] Table A.1 in Appendix A shows the selection procedure with the number of observations deleted in each step.

[9] For example, for more educated people (and especially for women) education may have a negative influence on weight due to higher frequency of weight monitoring (Wardle and Griffith, 2001), different life-styles, lower intertemporal discount rates. Presence of children may be associated with increase in weight and specific labor market outcomes (Lacobsen et al., 1999). Health problems are more frequent in obese people and they may also affect labor market performance (Andreyeva et al., 2005), while smoking is negatively correlated with labor productivity but also with weight (Molarius et al., 1997; Evans and Montgomery, 1994).

[10] Graphs are not shown, but are available upon request from the authors.

Table 1
Descriptive statistics of BMI, underweight, normal weight, overweight and obese

	BMI (kg/m^2)	Underweight (%)	Normal weight (%)	Overweight (%)	Obese (%)
Women					
Full sample	23.73	3.71	66.84	22.38	7.06
Austria	23.47	3.95	67.54	22.72	5.80
Belgium	23.09	4.25	74.59	15.03	6.12
Denmark	24.40	1.97	61.68	25.88	10.47
Finland	24.58	1.37	60.97	27.23	10.43
Greece	23.73	2.30	66.90	24.50	5.61
Ireland	23.84	2.91	66.39	23.70	7.00
Italy	22.74	6.52	71.99	18.10	3.34
Portugal	24.42	3.02	62.30	25.57	9.11
Spain	23.06	5.22	72.65	16.95	5.18
Men					
Full sample	25.75	0.39	44.97	44.70	9.94
Austria	25.65	0.04	48.45	41.56	9.94
Belgium	25.48	0.83	48.87	39.37	11.03
Denmark	25.56	0.64	46.95	42.60	9.81
Finland	25.95	0.24	44.04	43.94	11.78
Greece	26.09	0.19	38.45	52.67	8.70
Ireland	25.65	0.92	44.48	45.18	9.41
Italy	25.29	0.31	51.37	41.20	7.12
Portugal	25.85	0.27	43.42	46.61	9.69
Spain	26.20	0.46	38.87	47.84	12.83

Notes: Underweight, normal weight, overweight and obese workers are individuals with BMI lower than 18.5, between 18.5 and 25, between 25 and 30 and over 30, respectively, as indicated by WHO.

4. Ordinary least squares vs. quantile regression results

In this section we report the results of the empirical analysis carried out. As first step, we report the coefficients of the BMI classes obtained from OLS regressions for the pooled sample and for each country, by gender. The results are based on a sample population aged between 25 and 64 years (Tables A.2 and A.3).

According to Garcia and Quintana-Domeque (2006) restricting our attention to this age group should help to reduce the problem of measurement errors in BMI (difference between self-reported and objectively measured anthropometric indicators). In fact, as also proved by Thomas and Frankenberg (2002), the difference between self-reported and objectively measured BMI remains almost constant across individuals for people between 20 and 60, at least taking into account the available evidence for the US. Although our age group is slightly different from the one considered by Thomas and Frankenberg (2002), this should not represent a problem as we have tested that our results remain unchanged once the more restrictive sample based on individuals aged between 25 and 54 is used.[11] Moreover, as measurement error does not need to be the same across countries, country fixed effects are included in the pooled estimate to capture such heterogeneity.

In Tables 2 and 3 coefficients are reported under different model specifications for women and men, respectively. We start by estimating a parsimonious model in column 1 (reference model) where we do not control for health status and occupational dummies (but we control for all the covariates presented in Section 3), we then include only the health status indicator in column 2, only the occupational dummies in column 3 and finally both set of variables in column 4 to assess the robustness of the result to the inclusion of these potential endogenous variables. We propose this augmented specification procedure because as noticed by Garcia and Quintana-Domeque (2007), non-random sorting of individuals into different occupations might lead to sample selection bias if obese workers are more likely to work in specific occupations. Similar problems might arise when controlling for health status. For example, if obese individuals are more likely to be hired to work in occupations with lower wages, we might underestimate the effect of weight on wages after controlling for the occupational variables.[12] Looking at the results reported in Table 3, we can see that for men the coefficients barely changes across the different specifications, showing that the potential endogeneity problem associated with the health and occupational variables does not affect the estimates. The results for women are slightly different (see Table 2). While the inclusion of the health variable does not affect the weight coefficients (column 2), controlling for the occupational categories reduces the magnitude of the obesity coefficient but only for the pooled sample and for Finland and Denmark. The

[11] Using the Third National Health and Nutrition Examination Survey (NHANES III), which contains measures of true and self-reported weight and height (and therefore, BMI), to correct the self-reports of weight and height in the NLSY, Cawley (2004) shows that this does not seem to be a major problem. He finds that even if women tend to underreport their weights but not their heights, using reported BMI instead of corrected BMI does not alter significantly the estimates. Unfortunately, we do not have the possibility to apply a similar correction due to the lack of data on true measures of weight and height in Europe. Moreover, Sanz de Galdeano (2007) has compared aggregate obesity rates based on objective measures obtained by the WHO Global Database on Body Mass Index with the corresponding figures derived from the ECHP self-reported information on height and weight. She finds that the correlation coefficient between the ECHP and the WHO Global Database measures of obesity prevalence is reasonably high: 0.76 ($p < 0.05$) for men and 0.96 ($p < 0.01$) for women. Similar results are obtained when computing the Spearman rank correlation coefficients.

[12] We thank an anonimous referee for pointing this out.

Table 2
OLS regression estimates, underweight, overweight and obesity coefficients, pooled sample women (no obs. 30,313)

Women	(1)	(2)	(3)	(4)
Full Sample				
Obese	−0.08***	−0.08***	−0.06***	−0.05***
Overweight	−0.04***	−0.03***	−0.03***	−0.03***
Underweight	0.00	0.00	−0.01	−0.01
Austria				
Obese	0.02	0.02	0.03	0.03
Overweight	0.01	0.01	0.01	0.01
Underweight	0.06	0.06	0.06**	0.06**
Belgium				
Obese	−0.04	−0.04	−0.03	−0.03
Overweight	−0.03**	−0.03**	−0.03*	−0.03*
Underweight	−0.04	−0.03	−0.04*	−0.04
Denmark				
Obese	−0.07***	−0.07***	−0.05***	−0.05***
Overweight	−0.01	−0.01	−0.01	−0.01
Underweight	0.00	0.00	−0.04	−0.03
Finland				
Obese	−0.09***	−0.09***	−0.07***	−0.07***
Overweight	−0.04***	−0.04***	−0.04***	−0.04***
Underweight	0.00	−0.01	−0.01	−0.01
Greece				
Obese	−0.05*	−0.05	−0.06**	−0.05*
Overweight	−0.01	−0.01	−0.01	−0.01
Underweight	−0.02	−0.02	−0.01	−0.01
Ireland				
Obese	−0.06*	−0.06*	−0.04	−0.04
Overweight	0.00	0.00	0.00	0.00
Underweight	0.01	0.00	0.05	0.05
Italy				
Obese	−0.07***	−0.08***	−0.07***	−0.07***
Overweight	−0.04***	−0.05***	−0.04***	−0.04***
Underweight	−0.02	−0.02	−0.04	−0.04
Portugal				
Obese	−0.06*	−0.05	−0.04	−0.04
Overweight	−0.05***	−0.05***	−0.03*	−0.03*
Underweight	−0.01	0.01	0.01	0.02
Spain				
Obese	−0.13***	−0.13***	−0.10***	−0.11***
Overweight	−0.04**	−0.04**	−0.02	−0.02
Underweight	0.02	0.02	0.00	0.00

Notes: Model specification in column (1) is the reference model as it does not include health status (bad or good health status) and occupational dummies (Professionals, Clerks, Agriculture and Fishery occupations, Elementary occupations); in column (2) it includes only health status; in column (3) it includes only occupational dummies; finally, model in column (4) includes both health status and occupational dummies. Control variables in all the specifications include: country and time dummies, individual age, cohabitation status (living in couple or not), presence of children under twelve in the household, number of days absent from work, highest level of education completed (primary, secondary and tertiary), sector of activity (public or private), health insurance status (whether the health insurance is provided by the employer), and sector (agriculture, industry and services). Estimates are obtained using sample weights. Huber-White heteroskedasticity robust standard errors are adjusted in order to take into account the presence of multiple observations for each individual.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

coefficients for the other two categories of weight are almost constant. The result found for the group of women is compatible with the "selection effect" found by Lakdawalla and Philipson (2007), for which heavier women are selected into jobs requiring strength that are usually also less paid.[13] However, it is important to note that the wage penalties do not seem to be entirely explained by sorting of obese individuals into specific occupations and for many countries it does not affect the estimated at all.

[13] Lakdawalla and Philipson (2007) use a dataset containing detailed information at job level within occupational categories based on the Dictionary of Occupational Titles (DOT). Each occupational definition lists a title for the occupation, as well as a description of the occupation's skill requirements and demands. Unfortunately, if the "selection" interpretation is the correct one, we are convinced that the occupational variables, as available in the ECHP dataset, do not allow to properly account for the heterogeneous impact of the BMI status on wages, given that this selection occurs differently across job positions within the same occupation category. In turn, when controlling for occupational dummies the (true) effect of obesity on wages can be underestimated, while not controlling for occupational variables may cause an even more serious problem with the overestimation of the same effect. In this specific case, we decided to include occupational variables as this could at most provide an underestimation of our coefficients, thus providing prudential estimates of the effect of BMI on wages.

Table 3
OLS regression estimates, underweight, overweight and obesity coefficients, pooled sample men (no.obs. 47,374)

Men	(1)	(2)	(3)	(4)
Full Sample				
Obese	−0.01	−0.01	0.00	0.00
Overweight	0.01***	0.01***	0.02***	0.02***
Underweight	−0.13***	−0.12***	−0.12***	−0.11***
Austria				
Obese	0.02	0.03	0.04***	0.04***
Overweight	0.02**	0.02**	0.02**	0.02**
Underweight	0.44***	0.43***	0.37***	0.37***
Belgium				
Obese	0.01	0.01	0.02	0.02
Overweight	0.02**	0.02**	0.02**	0.02**
Underweight	−0.01	−0.01	0.00	0.00
Denmark				
Obese	0.02	0.01	0.03*	0.02
Overweight	0.01	0.01	0.02*	0.02*
Underweight	0.00	0.00	0.04	0.04
Finland				
Obese	−0.02	−0.01	−0.01	−0.01
Overweight	−0.01	−0.01	−0.01	−0.01
Underweight	−0.28**	−0.27**	−0.30**	−0.30**
Greece				
Obese	−0.04*	−0.04	−0.04**	−0.04**
Overweight	0.02	0.02	0.03**	0.03**
Underweight	−0.06	−0.06	−0.08	−0.08
Ireland				
Obese	0.01	0.01	0.01	0.01
Overweight	0.01	0.01	0.01	0.01
Underweight	−0.17***	−0.17***	−0.18***	−0.18***
Italy				
Obese	−0.05***	−0.05***	−0.05***	−0.05***
Overweight	0.01	0.01	0.01*	0.01*
Underweight	−0.22***	−0.21***	−0.22***	−0.21***
Portugal				
Obese	−0.01	−0.01	0.00	0.00
Overweight	0.02	0.02	0.03*	0.02*
Underweight	−0.05	−0.03	−0.03	−0.01
Spain				
Obese	−0.03	−0.03	−0.01	−0.01
Overweight	0.00	−0.01	0.00	0.00
Underweight	−0.19	−0.19	−0.11	−0.11

Notes: Model specification in column (1) is the reference model as it does not include health status (bad or good health status) and occupational dummies (Professionals, Clerks, Agriculture and Fishery occupations, Elementary occupations); in column (2) it includes only health status; in column (3) it includes only occupational dummies; finally, model in column (4) includes both health status and occupational dummies. Control variables include: country and time dummies, individual age, cohabitation status (living in couple or not), presence of children under twelve in the household, number of days absent from work, highest level of education completed (primary, secondary and tertiary), sector of activity (public or private), health insurance status (whether the health insurance is provided by the employer), and sector (agriculture, industry and services). Estimates are obtained using sample weights. Huber-White heteroskedasticity robust standard errors are adjusted in order to take into account the presence of multiple observations for each individual.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Based on the above evidence, we adopt the specification in column four as our reference model. Furthermore, as we are particularly interested in the relationship between obesity and wages, in what follow we will discuss only the results associated with the obesity coefficient, having in mind that the other weight categories are included as controls in the regression model. In order to allow for flexibility, we have estimated the model separately for men and women and by country. Furthermore, reported coefficients are robust to adjustments for heteroskedasticity. For the pooled sample the obesity coefficient is negative for women (see Table 2) and positive for men (see Table 3), although statistically significant (at 1%) only for women. This seems to suggest the existence of a wage penalty only for women at European level.

Country by country estimates provide a slightly different picture, showing the existence of some heterogeneity in the relationship between wages and weight across European countries especially for men.[14] Not for all countries in our dataset women seem to suffer from a wage penalty, given that in Austria and Belgium there is no evidence of an association between wage and obesity. Furthermore, whenever this association is statistically significant, the impact of the wage penalty is rather

[14] Our results are slightly different from those reported in Garcia and Quintana-Domeque (2007). This may depend from the different model specification adopted and from the sample selection procedure. Indeed, the conclusions remain very similar. We have not been able to compare our results with those of Brunello and d'Hombres (2007) as the authors do not present OLS estimates.

heterogeneous across countries, ranging from −5% in Denmark to −11% in Spain. As far as men are concerned, differences among countries are even more striking. In fact, we observe three different clusters: Belgium, Denmark, Finland, Ireland, Portugal and Spain which confirm the result of no statistical association from the pooled sample, Greece and Italy which show a wage penalty (−4% and −5%, respectively) and, finally, Austria which records a wage premium (4%).[15]

As discussed in Section 2, the whole literature on the relationship between wage and obesity has been based on a mean regression approach, which looks only at the role of obesity at the mean level of the wage, ignoring individual wage heterogeneity. However, it could be that obesity affects individual wages differently across the wage distribution. A way to overcome such limitation is to adopt a quantile regression approach that allows us to characterize the whole conditional distribution of wage. Indeed, we may expect that in the lowest points of the wage distribution workers perform manual activities that require effort and greater muscle mass. Similarly, in the highest points of the wage distribution intellectual activity is needed and obesity may not represent an issue. In the first case we should expect a positive effect of the obesity coefficient in the left tail of the wage distribution, while in the second case a not significant effect in the right tail. Alternatively, as suggested by Hamermesh and Biddle (1994), appearance may count more than responsibility and managerial skills at the top of the wage distribution (although mainly for women), and for this reason we might expect a negative obesity coefficient at least in the right tail of the wage distribution.

Tables 4 and 5 report the quantile regression estimates for the pooled sample, respectively, for women and men with both health and occupational variables included. What emerges is that while for women in Table 4 the QR estimates turn out to be not very different from the estimates computed at the mean, for men in Table 5 the opposite holds. Moreover, the effect of obesity for women is negative and statistically significant at 1% along the wage distribution, and in absolute terms slightly lower on the tails of the distribution (−4% at 15th, 25th and 85th percentile, respectively) compared to the central part (5%) (the full set of results is available in Table A.4) .

Differently from women, the effect of obesity for men is more heterogeneous across quantiles. In particular, men seem to suffer from wage penalty due to obesity (−2%) at 15th percentile, and enjoy a wage premium at (2%) at 50th and 75th percentiles, while the effect is not statistically significant in the remaining quantiles (see Table 5). These last results seem to contradict both the "obesity as an asset" and the Hamermesh and Biddle (1994) "appearance theory" hypotheses.

Looking at country specific estimates in Table 6, the heterogeneity in the statistical association between wages and obesity is even more pronounced. For women, in Ireland the wage penalty is found only in the left part of the wage distribution, in Greece only at the median of the wage distribution, in Italy the relationship is characterized by a reversed U-shaped curve with larger penalties on the tails. No regular patterns can be found in countries like Denmark, Finland and Spain, although coefficients vary quite a lot across quantiles (for example, in Finland, while the mean effect for women is equal to −7.0%, using quantile regression the effect ranges from −10.0% at 15th percentile to −4.0% at 85th percentile. For men the OLS results are not significant, while the quantile estimates show a significant penalty of 5% at 15th percentile). We tested the differences of the coefficients across quantiles. According to these tests we rejects the equality of most pair-wise comparisons of the β s in some countries (exceptions are Denmark, Ireland, Italy and Spain), and in case of the pooled model for almost all male coefficients. This suggests two conclusions: (1) countries are different in terms of wage-obesity relationship, and (2) within some countries the relationship between obesity and wage is different across quantiles.[16] In summary, these findings seem to suggest that it would be misleading to ignore the heterogeneity of the obesity effect across countries and along the wage distribution.

4.1. Are there alternative explanations to the statistical association between wage and obesity?

In the previous section we have found evidence of an important statistical association between wages and obesity. However, as suggested by Baum and Ford (2004), it is important to understand to what extent this association could be explained by one of the following three possible sources: (i) losses in productivity due to health problems; (ii) agents' myopic behavior; (iii) provision of health insurance by employers who discount higher health care costs for obese workers in the form of lower wages. We expect that if differences in wages between obese and non-obese workers are due to one of the above mentioned reasons, once controlled for them, the obesity coefficient should become statistically insignificant. Formally, to take into account the above mentioned hypotheses, we specify the model in the following way:

$$W_{i,t} = \beta_0 + \Sigma_{j=1}^{4}\beta_j \mathrm{BMI}_{j,i,t} + \gamma D_{i,t} + \delta D_{i,t}\mathrm{BMI}_{4,i,t} + \varphi X_{i,t} + \varepsilon_{i,t}, \quad \text{for} \quad i = 1, \ldots, N; \;\; t = 1, \ldots, T \tag{2}$$

where $D_{i,t}$ represents the variable of interest (productivity proxy, participation to training programs, and health insurance), $\mathrm{BMI}_{4,i,t}$ is the obesity category and $\mathrm{BMI}_{1,i,t}$, $\mathrm{BMI}_{2,i,t}$, and $\mathrm{BMI}_{3,i,t}$ are underweight, normo-weight, and overweight categories, respectively. Therefore, δ is our parameter of interest. In this section we test the significance of these hypotheses. Results are reported in Table 7.

[15] In absolute values these percentages are not negligible. For example, given a coefficient of 0.05 (as for women in the pooled sample), and assuming an annual salary of 30,000 euros, the penalty effect amounts to about 125 euros per month. Slightly higher values are obtained at country level for some countries (for example in Spain it reaches the highest value of 225 euros per month).

[16] A table with the full list of pair-wise comparison tests is available upon request.

Table 4
Quantile regressions estimates: pooled sample, women (no. obs. 30,313)

	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Obese	−0.04***	−0.04***	−0.05***	−0.05***	−0.04***
Overweight	−0.01**	−0.01**	−0.02***	−0.02***	−0.03***
Underweight	−0.03**	−0.03**	−0.01	0.02	0.02
Union	3.99***	3.99***	3.69***	3.68***	3.52***
Insurance	0.05***	0.05***	0.05***	0.06***	0.06***
Training	0.13***	0.12***	0.10***	0.09***	0.08***
Sickness days	−0.02	0.00	−0.01	0.00	0.00
Bad health status	0.00	0.00	−0.02	−0.04**	0.00
Age	0.03***	0.03***	0.03***	0.03***	0.03***
Age squared	0.00***	0.00***	0.00***	0.00***	0.00***
Private	−0.11***	−0.10***	−0.08***	−0.07***	−0.06***
Couple	0.03***	0.02***	0.01**	0.00	0.01
Children	0.01	0.00	0.01**	0.03***	0.03***
Secondary	0.17***	0.16***	0.16***	0.16***	0.16***
Tertiary	0.30***	0.29***	0.33***	0.38***	0.41***
Smoker	0.01**	0.02***	0.03***	0.03***	0.03***
Clerks	−0.12***	−0.13***	−0.15***	−0.19***	−0.20***
AgrFishery	−0.20***	−0.23***	−0.30***	−0.38***	−0.39***
Elementary	−0.21***	−0.23***	−0.27***	−0.33***	−0.35***
Agriculture	−0.15***	−0.14***	−0.16***	−0.09***	−0.07**
Industry	0.08***	0.06***	0.04***	0.04***	0.03***
Constant	−0.58***	−0.38***	−0.20***	0.00	0.09

Note: Control variables include also country and time dummies.
** Significant at 5%.
*** Significant at 1%.

4.1.1. Productivity hypothesis

In order to test whether obese workers earn less than non-obese workers because they are less productive, we interact the obesity dummy with a productivity proxy, namely the number of days of absence from work due to sickness. The ECHP asks respondents to report the number of days they were absent from work during the last four working weeks because of illness

Table 5
Quantile regression estimates: pooled sample, men (no. obs. 47,374)

	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Obese	−0.02***	0.00	0.02**	0.02***	0.01
Overweight	0.02***	0.02***	0.02***	0.02***	0.03***
Underweight	−0.12***	−0.16***	−0.12***	−0.11***	−0.03
Union	3.86***	3.63***	3.05***	2.67***	2.48***
Insurance	0.06***	0.05***	0.07***	0.06***	0.06***
Training	0.11***	0.11***	0.09***	0.10***	0.09***
Sickness days	−0.06***	−0.07***	−0.03*	−0.02	0.00
Bad health status	−0.09***	−0.07***	−0.09***	−0.05***	−0.05***
Age	0.04***	0.03***	0.03***	0.03***	0.04***
Age squared	0.00***	0.00***	0.00***	0.00***	0.00***
Private	−0.07***	−0.05***	−0.03***	0.00	0.01
Couple	0.07***	0.07***	0.08***	0.08***	0.08***
Children	0.03***	0.02***	0.03***	0.03***	0.02***
Secondary	0.12***	0.12***	0.12***	0.15***	0.15***
Tertiary	0.22***	0.24***	0.28***	0.34***	0.36***
Smoker	−0.03***	−0.03***	−0.02***	−0.01**	−0.01*
Clerks	−0.10***	−0.12***	−0.14***	−0.14***	−0.16***
AgrFishery	−0.12***	−0.14***	−0.18***	−0.21***	−0.22***
Elementary	−0.16***	−0.18***	−0.21***	−0.22***	−0.24***
Agriculture	−0.28***	−0.22***	−0.17***	−0.12***	−0.14***
Industry	0.07***	0.05***	0.03***	0.02***	0.02***
Constant	−0.54***	−0.30***	0.16***	0.32***	0.39***

Note: Control variables include also country and time dummies.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 6
Quantile regression estimates: obesity coefficients by country

	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Women					
Austria	0.03	0.02	−0.02	0.07**	0.05*
Belgium	−0.01	−0.03	−0.07**	−0.01	0.00
Denmark	−0.06***	−0.07***	−0.05***	−0.05***	−0.06***
Finland	−0.1***	−0.05***	−0.06***	−0.05***	−0.04**
Greece	−0.03	−0.04	−0.06**	0.00	−0.01
Ireland	−0.06**	−0.05*	−0.03**	0.00	−0.01
Italy	−0.06**	−0.06**	−0.03	−0.05**	−0.08***
Portugal	0.01	0.00	−0.04*	−0.03	−0.03
Spain	−0.12***	−0.12***	−0.1***	−0.11***	−0.11***
Men					
Austria	0.02	0.04***	0.06***	0.06***	0.07***
Belgium	0.05**	0.04**	0.02	−0.02	−0.02
Denmark	0.04**	0.03	0.03***	0.04***	0.02
Finland	−0.05***	−0.02	0.00	0.01	0.03
Greece	−0.04*	−0.06***	−0.02	0.00	0.00
Ireland	0.00	0.01	0.02	0.04	0.06***
Italy	−0.06***	−0.06***	−0.03***	−0.03**	−0.02
Portugal	−0.06***	0.02	0.03*	0.04	0.04
Spain	−0.01	−0.04**	−0.02	−0.02	0.00

Note: Coefficients for underweight and overweight dummies are not shown. Control variables are as in Table 2.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

or other reasons. It should be noted that this measure includes absent episodes due to illness and to any other reason, so it is not possible to isolate the impact of obesity-related illness episodes. Looking at Table 7, for the pooled sample we find that health limitations do not affect obese workers' wages differently from non-obese workers' and the obesity wage penalties remain unchanged for both men and women (panel A). This suggests that obesity influences wages through a channel different from productivity losses due to health limitations.[17]

4.1.2. Myopic behavior hypothesis

According to the agents' myopic behavior hypothesis, obese workers heavily discount the future by caring less about obesity-related health problems and invest less in human capital accumulation (less training), thus generating a flatter wage profile.[18] We test this hypothesis by interacting the obese dummy with the training dummy.[19] The results (Panel B) show that while investment in training significantly increases wages for men and women, the interaction obesity-training is not significant for both women and men, while the obesity coefficients are slightly lower at the tail of the distribution for women and not significant anymore in the center of the distribution (50th and 75th percentiles) for men with respect to our reference model. This indicates that, at least for women, agents' myopic behavior is not what drives the negative relationship between weight and wages. On the contrary, for men by netting out the myopic behavior effect, the wage penalty due to obesity in the center of the distribution disappears.[20]

4.1.3. Health care insurance costs hypothesis

We investigate whether the observed wage differential between obese and non-obese workers in European countries can be explained by the costs of health care insurance covered by the employer and charged on employees' wage. We test this hypothesis by interacting the obesity dummy with the health insurance dummy and we find that the interaction coefficient is positive but not significant both for men and women (Panel C). As found for men in the myopic behavior hypothesis, controlling for health care insurance costs the negative association between wage and obesity disappears in the center of the distribution, while for the female group we can notice a small increase in the wage penalty in the bottom part of the distribution

[17] We should keep in mind that obesity might affect productivity in ways that are not as easily measured. The negative effect of obesity on appearance, for example, can affect confidence and communication, thereby influencing productivity. Mobius and Rosenblat (2004) estimate that confidence accounts for approximately 20% of the beauty premium. Persico et al. (2004) hypothesize that height increases the chances that teenagers participate in social activities, such as nonacademic clubs and sports. This participation, in turn, helps them to learn skills that are rewarded by employers and might enhance productivity.
[18] Komlos et al. (2004) discuss the role of time preference as determinant of obesity epidemic. Using the savings rate and consumer debt as indicators of the rate of time preference, they find some empirical evidence for the US and OECD countries confirming the link between obesity and time preference.
[19] It must be noted that, unfortunately, this variable does not allow to disentangle decisions to invest in training taken by employers and those taken by employees, thus potentially weakening the possibility to discriminate between the myopic behavior hypothesis and the pure discrimination hypothesis. We thank an anonymous referee for pointing this out.
[20] Baum and Ford (2004) use the experience variable as a proxy for engagement in training activities. Our data allow to use directly the variable training. The ECHP does not provide a specific variable "years of experience on the labor market". It provides only the variable tenure ("years of experience in the current job"), but this variable has a large number of missing data (about 9000 observations in the pooled sample). Therefore, we prefer not to use it.

Table 7
Quantile regression estimates with interactions, pooled sample

	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Women					
Base model					
Obesity	−0.04***	−0.04***	−0.05***	−0.05***	−0.04***
(Panel A) Base + sickness interaction					
Obesity	−0.04***	−0.04***	−0.05***	−0.05***	−0.04**
Sickness days	−0.02	−0.01	−0.02	0.00	0.00
Obesity × sickness	0.02	0.04	0.03	0.00	−0.07
(Panel B) Base + training interaction					
Obesity	−0.03*	−0.04**	−0.05***	−0.05***	−0.03*
Training	0.13***	0.12***	0.10***	0.09***	0.08***
Obesity × training	−0.01	−0.01	0.00	0.00	−0.02
(Panel C) Base + insurance interaction					
Obesity	−0.06***	−0.05***	−0.06***	−0.04**	−0.03*
Insurance	0.04***	0.05***	0.05***	0.06***	0.06***
Obesity × insurance	0.04	0.01	0.02	−0.01	−0.02
(Panel D) Base + all interactions					
Obesity	−0.05**	−0.04**	−0.06***	−0.05**	−0.03
Sickness days	−0.02	−0.01	−0.02	0.00	0.00
Training	0.13***	0.12***	0.10***	0.09***	0.08***
Insurance	0.04***	0.05***	0.05***	0.06***	0.06***
Obesity × sickness	0.03	0.04	0.03	0.01	−0.05
Obesity × training	−0.04	−0.02	−0.01	0.00	0.00
Obesity × insurance	0.04*	0.02	0.03	−0.01	−0.02
Men					
Base model					
Obesity	−0.02***	0.00	0.02***	0.02***	0.01
(Panel A) Base + sickness interaction					
Obesity	−0.02***	0.00	0.02**	0.02**	0.01
Sickness days	−0.06***	−0.06***	−0.03*	−0.02	0.00
Obesity × sickness	0.00	−0.06	−0.01	0.00	−0.03
(Panel B) Base + training interaction					
Obesity	−0.03***	−0.01	0.01	0.01	0.00
Training	0.11***	0.11***	0.09***	0.09***	0.08***
Obesity × training	0.02	0.02	0.01	0.03*	0.02
(Panel C) Base + insurance interaction					
Obesity	−0.02***	0.00	0.01	0.01	0.00
Insurance	0.06***	0.05***	0.07***	0.06***	0.06***
Obesity × insurance	0.00	0.00	0.01	0.03*	0.02
(Panel D) Base + all interactions					
Obesity	−0.03***	−0.01	0.01	0.00	−0.01
Sickness days	−0.06***	−0.06***	−0.03*	−0.02	0.00
Training	0.11***	0.11***	0.09***	0.09***	0.08***
Insurance	0.06***	0.05***	0.07***	0.06***	0.06***
Obesity × sickness	0.00	−0.08	−0.01	−0.01	−0.03
Obesity × training	0.02	0.03*	0.01	0.02	0.02
Obesity × insurance	0.00	−0.01	0.01	0.02	0.02

Note: Control variables are as in Table 2 plus underweight and overweight dummies.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

and a small reduction in top part. Overall, this result should not come as a surprise given that the countries in our sample are characterized by universal coverage of health care services and that health insurance provided by the employer covers additional services not included in the public insurance. As for the previous hypotheses, this finding seems to indicates that health care insurance costs are not able to explain the negative relationship between weight and wages.

To complete this analysis, we have run a new model in which all these hypotheses have been considered jointly. Results are reported in Panel D in Table 7.[21] Concerning men, we observe an increase in the wage penalty in the first percentile, while the coefficients at the 50th and 75th percentiles loose their significance. For women, we observe a small increase in the wage penalty in the first and third quantiles.

We finally test whether the obesity coefficients in models with interactions (Panel D) and without are statistically different and we find that none of them are statistically significat at 5% level in the pooled sample. At country level, there are very few cases in which the interaction terms change significatively the obesity coefficients in some quintiles.[22] Given that none of these hypotheses seem to be able to change substantially the significance of the obesity coefficients, our findings

[21] The full set of results with all other covariates and results country by country are available upon request.
[22] The full set of results is available upon request.

could suggest the existence of a pure discriminatory effect, although not conclusive in the sense we are not estimating a causal effect.

4.2. The role of labor market institutions

As recently outlined by Freeman (2008), there is a widespread consensus on the fact that institutions have a major impact on the distribution of income. Among them, the presence of labor market institutions plays a major role in shaping it. Garcia and Quintana-Domeque (2007) have studied this issue looking at how the presence of unions, their membership diffusion, the level of bargaining coverage and at what level (centralized and/or coordinated) can affect the relationship between obesity and wages. In this section we try to assess whether labor market institutions may help to understand the different results obtained in terms of the relationship between obesity and wages across countries by means of three indicators of labor market regulations: trade union density, bargaining governability, and degree of employment protection legislation (EPL) as reported in Table A.5 in Appendix A. In particular, we expect that in countries with high levels of union density, bargaining governability and EPL, where the wage setting is more controlled and employers and firms play a minor role in the wage setting, the relationship between obesity and wages should not be significant or small in size. Unfortunately, we cannot empirically test these hypotheses in a regression framework for two main reasons: (i) the ECHP data set does not provide union participation at individual level; (ii) data on level of union density, bargaining governability, and EPL are obviously collected at country level and time invariant. However, we can provide an indirect evidence of the relationship between labor market institutions and wage penalty differences across countries by means of Spearman correlation coefficients.[23]

Table 8 shows the ranking of countries according to the size of the obesity effect as obtained in Table 6. Two main results emerge from this table: (1) with few exceptions the signs of the correlation coefficients are all negative, (2) correlations are different across quantiles and across labor market institution indicators. A negative sign is a symptom that labor market institutions foster the use of the obesity factor as a wage penalty, thus contrary to be the theoretical predictions. Negative signs are recorded for women at almost all quantiles of the wage distribution and for all indicators. For men a positive sign is found only for EPL at all points in the wage distribution. This last case seems to be the only one in our analysis where the empirical analysis is in accordance with the theoretical prediction. The highest value of the correlation is found for the lowest quintile. Although obtained through a different methodology and adopting slightly different labor market indicators, these results match, at least for women, those obtained by Garcia and Quintana-Domeque (2007) on the same data.

5. Dealing with the endogeneity problem

As already discussed in previous sections, the results produced so far cannot be interpreted as causal relationship from obesity to wages. In an effort to add robustness to our previous results and to compare them with what has been presented in some of the literature so far, here below we replicate our analysis by employing an IV approach. In what follows we first review some of the main contributions in this field and then present our estimation strategy based on Instrumental Variable Quantile Regression (IVQR) and the results obtained.

5.1. The obesity endogeneity problem in the empirical literature

Standard OLS techniques may yield biased estimates of the relationship between wage and obesity for at least three reasons. First, unobservable individual effects associated to genetic and non-genetic factors, such as ability and parental background, might be correlated both with earnings and the respondent's body mass index. Second, a problem of reverse causality might exist. For instance, the quality and the quantity of food might determine how an individual behaves, her level of productivity and inventiveness at work, and her earning potentialities, but, at the same time, individual working position and wages might influence her quality and quantity of food. Finally, the BMI can be measured with errors, as researchers rely on self-reported measures of weight and height.[24] In this case, the error term is correlated with the variable of interest by construction, generating inconsistent estimates.

Several studies have dealt with the endogeneity problem using alternative identification strategies. Sargent and Blanchflower (1994), Gortmaker et al. (1993), and Averett and Korenman (1996) address reverse causality by replacing the contemporaneous BMI with its lagged value. However, the validity of this strategy relies on the hypothesis of independence between the lagged BMI and the residual, which is unlikely to be true especially in presence of unobserved individual effects. Baum and Ford (2004), Cawley (2004), Cawley and Danziger (2005) and Sanz de Galdeano (2007) use fixed effect estimators to control for unobservable individual effects. This identification strategy does show some drawbacks. In particular, as also

[23] Garcia and Quintana-Domeque (2007) analyze the relationship between labor outcomes (employment and wage) and collective bargaining coverage (the number of employees covered by a collective agreement over the total number of employees) through a simple graphical analysis, where they plot labor market institutions indicators on the *X*-axis and obesity labor market outcomes on the *Y*-axis. They find a positive association between collective bargaining coverage and the probability of being unemployed with respect to being employed for women, but no clear relationship for men. Moreover they find a strong positive association between collective bargaining coverage and wage gaps for women but no clear relationship for men.

[24] See also footnote 10 for a discussion about this issue.

Table 8
Spearman rank correlation coefficients by quantiles

	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Women					
Union density	−0.092	−0.125	−0.217	−0.125	−0.358
Bargaining governability	−0.476	−0.131	0.036	−0.452	0.298
EPL	−0.325	−0.35	−0.05	−0.025	−0.025
Men					
Union density	−0.400	−0.408	−0.342	−0.333	−0.083
Bargaining governability	−0.214	0.048	−0.440	−0.714	−0.286
EPL	0.533	0.292	0.058	0.100	0.300

Note: Each cell in the table reports the Spearman correlation coefficient between the obesity coefficient for each quantile at country level and the corresponding ranking for each labor market indicator. For example, the value reported at the cross between the 15th quantile and the row with union density represents the Spearman correlation coefficient between the obesity coefficients recorded for each country in that quantile and the ranking of the union density variable.

noted by Garcia and Quintana-Domeque (2007), a fixed effect strategy does not solve the reverse causality problem. In addition, there is a clear trade-off between consistency of the estimates obtained with longer panel and plausibility of the unobservables' time invariance.

Many researchers have instead adopted an instrumental variable approach to deal with the problem of endogeneity, using different instruments. Pagan and Davila (1997) choose as instrument indicators of health problems, such as self-esteem and family poverty. Cawley (2000, 2004) adopts the BMI of "biological" family members (including parents', siblings' and children' body mass index) and Cawley et al. (2005) use the weight of a child or of a parent, under the assumption that the BMI of a biological family member does not affect the respondent's wage directly. Morris (2006) adopts the average BMI and prevalence of obesity across individuals living in the same health authority area as instruments. Greve (2007) uses information on whether the individuals' parents have ever taken medication related to obesity or obesity-related diseases (namely hypertension and Type 2 diabetes) and their mortality cause. Lundborg et al. (2007) choose as instruments the presence of other obese persons in the household, being an oldest child, and having sisters only. Finally, Brunello and d'Hombres (2007) solve the endogeneity problem by considering the "biological" BMI (computed as average of all household members' BMI) as instrument. The main drawback with the IV approach is that two conditions have to be satisfied to ensure the validity of an instrument. It must be correlated with the endogenous variable and uncorrelated with the outcome's residuals. While the first condition can be easily tested, with respect to the second condition only indirect evidence can be provided given that no formal procedure exists to test for absence of correlation between the instrument and wage residuals.

In order to overcome the difficulty of finding suitable instruments, Sousa (2005) uses a propensity score matching approach. However, since this procedure implies to find comparable individuals within the same dataset it might lead to reduce enormously the sample size. A similar problem is found by Behrman and Rosenzweig (2001) and Conley and Glauber (2007) when using information on siblings and twins to remove the common household effect due to both genetic and non-genetic factors, given that the number of households with at least two children living in is limited and, therefore, it may create problems of representativeness.

With the data in our hands, we believe that the IV approach is the most convincing (among those mentioned above) to deal with the endogeneity problem, despite its drawback concerning the choice of instruments. In order to better understand the limit of "biological" BMI we should notice that the residual of the wage Eq. (1) can be decomposed as:

$$\varepsilon_{i,t} = G_{i,t} + NG_{i,t} + \nu_{i,t} \tag{3}$$

where $G_{i,t}$ is the genetic component, $NG_{i,t}$ is the non-genetic component and $\nu_{i,t}$ is a residual, i.i.d. over individuals and time.

Several studies reviewed in Cawley (2004) have shown that the correlation of weight within household members is due to genetic factors rather than to environmental influences. More specifically, according to Grilo and Pogue-Geile (1991), environmental experiences shared among family members are not important in determining individual differences in weight. Therefore it is unlikely that biological BMI (bBMI) is correlated with the unobserved non-genetic errors and it can be safely assumed that $\mathrm{Corr}(\mathrm{bBMI}_{i,t}, NG_{i,t}) = 0$. Unfortunately, the error terms of the wage and obesity equations could be still correlated if unobservable genetic factors affecting individual earnings are correlated to transmitted genetic variation in weight ($\mathrm{Corr}(\mathrm{bBMI}_{i,t}, G_{i,t}) \neq 0$), although this event may not be very likely when analyzing labor market outcomes (Cawley, 2004).

Ideally, the best strategy to control for unobserved genetic factors is to use same-sex siblings or twins' weight as an instrument. In practice, apart from the reduction in sample size mentioned above, it has some additional drawbacks: (i) it is not possible, in all surveys, to identify siblings because they may have left the original households; (ii) in our specific case, it is likely that if they live in the same household it is because they are still at school and/or not working, thus not useful for identifying the relationship of interest.

Table 9
IV and IVQR regression estimates, obesity, overweight and underweight coefficient

	IV	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Women						
Obesity	−0.065*	0.144	0.066	0.154	−0.156**	−0.206**
Overweight	−0.186*	0.196	0.411	0.195	0.317	−0.216*
Underweight	−0.129	1.478	2.593	1.674	4.152	3.011
F-test first stage			$F(31, 10760) = 17.17$			
Obesity equation			Prob > $F = 0.0000$			
F-test first stage			$F(31, 10760) = 20.97$			
Overweight equation			Prob > $F = 0.0000$			
F-test first stage			$F(31, 10760) = 12.92$			
Underweight equation			Prob > $F = 0.0000$			
Men						
Obesity	−0.337**	0.559	0.566	0.384	−0.224*	−0.044**
Overweight	−0.061	−0.834	−0.662	−0.747	−0.759*	−0.602
Underweight	−0.922	−2.569	−7.302	−7.322	−3.071	−4.359
F-test first stage			$F(31, 19276) = 18.54$			
Obesity equation			Prob > $F = 0.0000$			
F-test first stage			$F(31, 19276) = 19.38$			
Overweight equation			Prob > $F = 0.0000$			
F-test first stage			$F(31, 19276) = 4.42$			
Underweight equation			Prob > $F = 0.0000$			

Notes: Control variables include: time and country dummies, individual age, cohabitation status (living in couple or not), presence of children under twelve in the household, health status (bad or good health status) number of days absent from work, highest level of education completed (primary, secondary and tertiary), sector of activity (public or private), health insurance status (whether the health insurance is provided by the employer), sector (agriculture, industry and services) and occupational category (Professionals, Clerks, Agriculture and Fishery occupations, Elementary occupations).
* Significant at 10%.
** Significant at 5%.

Given the alternatives provided in the literature and the availability of the information included in the ECHP dataset, we decide to use the ‘‘biological’’ BMI as instrument, as Brunello and d’Hombres (2007) proved to be reliable on the same dataset. The ‘‘biological’’ BMI (from which we have derived the four categories—biological underweight, biological normo-weight, biological overweight, and biological obese) averages out all the available individual body mass index of the family members biologically related who completed the questionnaire.[25] However, compared to previous studies we innovate by adopting an Instrumental Variable Quantile Regression (IVQR) approach.

5.2. The instrumental variable quantile approach

As discussed by Blundell and Powell (2003) and Lee (2007), there are three major alternative approaches to endogenous quantile regression models, namely the *instrumental variable* (IV) approach (Hong and Tamer, 2003; Chen et al., 2003; Honoré and Hu, 2004; Chernozhukov and Hansen, 2005, 2006), the *fitted value* approach (Amemiya, 1982; Powell, 1983), and the *control function* approach (Chesher, 2003; Ma and Koenker, 2006; Blundell and Powell, 2005; Lee, 2007).[26] In this paper, we adopt an IV approach, following Chernozhukov and Hansen (2005, 2006), because their estimation approach is computationally convenient to our specific purpose, simple to implement and it leads to a testing procedure which is robust to the presence of week instruments.[27] According to them, an Instrumental Variable Quantile Regression (IVQR) model can be described in formal terms as:

$$Y = D'\alpha(U) + X'\beta(U) \tag{4}$$

$$U|X, Z \sim \text{Uniform}(0, 1)$$

$$D = \delta(Z, X, V) \tag{5}$$

[25] The choice of an instrument is often a matter of debate in the empirical literature especially for the impossibility of testing the validity of the exclusion restrictions and we are aware that our instrument is far from perfect. In other words, average BMI for family members might affect individual wages not only through individual BMI but also through other factors that enter directly into the wage regression, like education as correctly pointed out by one referee. For instance, average BMI for family members might be related to average educational level for family members. In turn, average educational level for family members is likely to pick up average ability for family members, which is related to individual ability. Therefore, individual ability is related to individual wages. In this case, average BMI for family members would not satisfy the exclusion restriction. To check whether such a (specific) criticism is relevant, we have performed we have also run the IVQR analysis controlling for average educational level for family members but the obesity coefficients results do not change quantitatively and qualitatively.

[26] For an exhaustive review of endogenous quantile regression models and their differences see Lee (2007).

[27] For more details see Chernozhukov and Hansen (2005, 2006), from which this section heavily draws.

Table 10
Quantile regression estimates for the restricted sample: obesity, overweight and underweight coefficients

	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Women					
Obesity	−0.051*	−0.064**	−0.060***	−0.053**	−0.020
Overweight	0.001	−0.017*	−0.020**	−0.027**	−0.023*
Underweight	−0.033	−0.026	0.019	0.040	0.010
Men					
Obesity	0.012	0.014	0.021	0.014	0.020
Overweight	0.032***	0.027***	0.028***	0.033***	0.036***
Underweight	0.001	−0.039	−0.036	0.052	0.088

Notes: Control variables are as in Table 2.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

where V is statistically dependent on U

$$\tau \mapsto D'\alpha(\tau) + X'\beta(\tau) \tag{6}$$

strictly increasing in τ.

In these equations Y is the scalar outcome variable of interest (the log of the hourly wage), U is a scalar random variable that aggregates all of the unobserved factors affecting the structural outcome equation, D is a vector of endogenous variables, where V is a vector of unobserved disturbances determining D and correlated with U, Z is a vector of instrumental variables independent from the disturbance U and correlated with D, X is a vector of included control variables. We refer to $Y \leq S_Y(\tau|D,X)$ as the structural quantile equation. At the heart of the model is *similarity*, a generalization of rank invariance assumption. The assumption of *similarity* states that given the information (Z,X,V) the expectation of U does not vary across the endogenous state D. It is a key identification device. From Eqs. (4)–(6), the event $Y \leq S_Y(\tau|D,X)$ is equivalent to the event $\{U < \tau\}$. It follows from Eq. (4) that

$$P[Y \leq (S_Y(\tau|D,X)|Z,X] = \tau \tag{7}$$

The moment equation given in (7) provides a statistical restriction that can be used to estimate the structural parameters α and β. Eq. (7) is equivalent to the statement that 0 is the τ th quantile of random variable $Y - S_Y(\tau|D,X)$ conditional on (Z,X):

$$0 = Q_{Y-S_Y(\tau|D,X)}(\tau|Z,X) \tag{8}$$

for each τ. We want to find an $S(\tau|D,X)$ such that 0 is the solution to the quantile regression of $Y - S_Y(\tau|D,X)$ on (Z,X):

$$0 = \arg\min_{f \in (F)} E_{\rho_\tau}[(Y - S_Y(\tau|D,X) - f(Z,X))], \tag{9}$$

where F is the class of measurable functions of (X,Z).

Considering a finite sample analog for the above procedure, the conventional quantile regression objective function can be defined as

$$Q_n(\tau,\alpha,\beta,\gamma) := \frac{1}{n}\sum_{i=1}^{n}\rho_\tau(Y_i - D_i'\alpha - X_i'\beta - Z_i'\gamma)V_i \tag{10}$$

where D is a dim(α)-vector of endogenous variables, X is a dim(β)-vector of exogenous explanatory variables, $Z_i \equiv (f(X_i,Z_i))$ is a dim(γ)-vector of instrumental variables such that $\dim(\gamma) \geq (\dim(\alpha))$. We set $V_i = 1$. To find an estimate for $\alpha(\tau)$, we will look for a value α that makes the coefficient on the instrumental variable $\hat{\gamma}(\alpha,\tau)$ as close to 0 as possible. Formally, let

$$\hat{\alpha}(\tau) = \arg\inf_{\alpha \in (A)}[W_n(\alpha)], \quad W_n(\alpha) := n[\hat{\gamma}(\alpha,\tau)']\hat{A}(\alpha)[\hat{\gamma}(\alpha,\tau)] \tag{11}$$

$A(\alpha)$ is set equal to the inverse of the asymptotic covariance matrix of $\sqrt{n}(\hat{\gamma}(\alpha,\tau) - \gamma(\alpha,\tau)$, where $W_n(\alpha)$ is the Wald statistic for testing $\gamma(\alpha,\tau) = 0$. The parameter estimates are then given by $\hat{\theta}(\tau) := (\hat{\alpha}(\tau), \hat{\beta}(\tau)) : (\hat{\alpha}(\tau), \hat{\beta}(\hat{\alpha}(\tau),\tau))$. In practice, for each probability index τ of interest, α and β are computed as follows. First define a set of values α_j, $j = 1,\ldots,J$, and run the ordinary quantile regression of $Y_i - D_i'\alpha_j$ on X_i and Z_i to obtain coefficients $\hat{\beta}(\alpha_j,\tau)$ and $\hat{\gamma}(\alpha_j,\tau)$. Then save the inverse of the variance–covariance matrix of $\hat{\gamma}(\alpha_j,\tau)$ to use as $\hat{A}(\alpha_j)$ in $W_n(\alpha_j)$, that becomes a Wald statistic for testing $\gamma(\alpha_j,\tau) = 0$. Finally, choose the value $\hat{\alpha}(\tau)$ that minimizes $W_n(\alpha)$. The estimate of $\beta(\tau)$ is then given by $\hat{\beta}(\hat{\alpha}(\tau),\tau)$.

5.3. Results from the IV quantile regression approach

In Table 9 we report the IV (column 1) and IVQR (columns 2–6) estimates for the pooled sample, for which the values of the *F*-test for the joint significance of the excluded instruments in the first stage regression, for both male and females, pass the threshold value of 10 (as the rule of thumb suggested by Staiger and Stock, 1997). At country level the situation is, instead, more problematic, given that for both samples the instruments turned out to be weak. We therefore decided not to report them.[28] First of all, we note that the IV obesity coefficients (column 1) are negative for both male and female, even if for male the effect is much larger in size. But if we look at the effect of obesity over the entire wage distribution, the story is much different, in that the negative effect is found only in the highest quantiles for both the samples. Moreover, if we compare the IVQR and the QR coefficients, interesting differences emerge or show up.... The obesity estimate for women is significant and very large in size (15–20%) only in the highest quantile, while it was significant all along the distribution and much lower in the QR case. Similarly, striking differences also appear between QR and IVQR for men. In fact, while in the QR case the obesity penalty was significant below the 25th percentile, in the IVQR approach it turns out to be significant starting at the 75th percentile. When we tested for the difference between the QR and IVQR coefficents we failed to reject the equality between the QR and the IVQR estimates (available upon request from the authors), apart for the 25th quantile in the male sample where the difference is significant at 5%. However, it is hard to say if it depends on lack of differences among coefficients or on large standard errors.[29] For this reason, we keep on investigating the possible reasons for the difference between QR and IVQR coefficients.

The differences between QR and IVQR estimates may arise from the combination of two sources. The first, and most obvious, has to do with the reduction of the sample size, due to the construction of the instrument (see Table A.1 in Appendix A). The second has to do with the different estimation technique (QR vs. IVQR). In order to separate these two effects, we have first compared the QR estimates based on the unrestricted sample with the QR estimates based on the restricted sample and then these latter with the IVQR estimates. As expected, comparing the unrestricted QR estimates (see Tables 4 and 5) with the restricted QR estimates reported in Table 10 we can see that selection bias determines sizeable differences both in magnitude and significance across the two samples.

In fact, it must be noticed that in the case of single households with deceased parents, couples with no children, couples with children aged less than sixteen, or households whose components are not biologically related (step, adopted and foster child, son and daughter in law, or just household's components not related), it is not possible to calculate the biological BMI and thus these observations need to be excluded from the sample. In our specific case, this procedure leads to a sharp reduction of the observations from 77,687 to 30,100.[30] As noted by Brunello and d'Hombres (2007) this could lead to select a non-random sample of the population. Indeed, comparing the initial sample to the restricted sample we actually find that, while the average BMI in the two samples is very close, individuals in the restricted sample are on average younger, less educated, with lower average wage and belong to larger households. Moreover, individuals in Southern Europe countries have a higher probability of being included in the restricted sample because these countries are characterized by larger household size with respect to Northern Europe countries.[31] Finally, comparing the IVQR estimates reported in Table 9 with the QR estimates for the restriced sample in Table 10, we can see that the differences in the coefficient estimates are stressed even further.

In conclusion, in light of this lack of robustness in the estimates, the concern around the instrument adopted, and the impossibility to statistically prove that QR and IVQR estimates are different, we suggest caution when interpreting the relationship between obesity and wages as causal in the ECHP data.

6. Conclusions

In this paper we have investigated the statistical association between obesity and wages along the wage distribution and, contrary to most work on this topic, we have taken care of the existing country heterogeneity by modeling the relationship between obesity and wages country by country. In the first part of the paper we have produced evidence of a negative statistical relationship, computed at the mean, between wages and obesity, and that this relationship is far from being

[28] The full set of results is available upon request.

[29] We have used the following strategy. According to these results (available upon request from the authors) we have first computed β_{QR} and β_{IVQR} for each quantile and boostrapped *M* times. Then, for each bootstrap value we have computed (i) the difference $(\beta_{\text{QR},m} - \beta_{\text{IVQR},m})$, (ii) the standard deviation of these *M* differences and (iii) have applied the formula: $(\beta_{\text{QR},m} - \beta_{\text{IVQR},m})/\text{sd}(\beta_{\text{IVQR},m} - \beta_{\text{IVQR},m})$. This procedure has been replicated for each quintile.

[30] See Table A.1 for the selection procedure. Descriptive statistics of the reduced sample are available upon request.

[31] Unfortunately, testing for selection bias is not an easy task when using IVQR, nor it is always possible to test for it. In fact, the standard two-step approach suggested by Wooldridge (2002) and applied by Brunello and d'Hombres (2007) cannot be adopted in the IVQR framework. A possible alternative could be represented by a test proposed by Buchinsky (2001), but unfortunately it relies on the assumption that the vector of Xs is uncorrelated with the error term. This represents a strong assumption in our context, given that it remains valid only if quantiles are parallel (or, equivalently, that the β s are equal across quantiles) as proven by Melly and Huber (2007). The test we have carried out rejects the equality of most pair-wise comparisons of the β s (results are available upon requests) in many countries (exceptions are Denmark, Ireland, Italy and Spain), and in case of the pooled model for almost all male coefficients. Based on these results, we decided not to test for selection bias.

homogeneous across countries and across wage quantiles. These results show that the mean and quantile approaches lead to different interpretation of the phenomenon under scrutiny, partly in line with the results obtained by Fahr (2006) and Garcia and Quintana-Domeque (2007).

Considering the pooled data, the relationship seems to be negative and significant all over the distribution for women and negative and significant only in the bottom part of the distribution for men, suggesting that males with less rewarding jobs are also more hit by obesity status. Furthermore, it was not possible to identify common patterns across countries that could be interpreted as environmental, cultural or institutional factors affecting the relationship between wages and obesity as instead suggested by Brunello and d'Hombres (2007).

We have also shown that this negative relationship holds even after controlling for decrease of productivity due to health problems, agents' myopic behavior, and provision of health insurance by employers, thus suggesting that residual wage differences might be due to employer discrimination. Whether this discrimination could be more in the vein of "taste" discrimination (Becker, 1957) or of "statistical discrimination" (Aigner and Cain, 1977) requires a different analysis that is beyond the scope of this work.[32]

Finally, in an attempt to control for endogeneity and to interpret our estimates as causal relationships, we have employed an IVQR technique. Unfortunately, the results we obtain can hardly be considered as conclusive for two main reasons: (i) we cannot prove that the instrument used is orthogonal to the error term in the wage equation, and (ii) the construction of the instrument imposes a significant and non-random cut in our sample that prevents us from comparing the QR and IVQR estimates. In conclusion, in the light of this lack of robustness in the estimates, and the concern around the instrument adopted, we suggest caution when interpreting the relationship between obesity and wages as causal with the ECHP data.

Why this discrimination exists in some quintiles and not in others or in all quantiles but with different intensity is not yet clearly understood. Several laboratory studies (see Roehling, 1999) analyze common stereotypes of obese workers that prove how obese workers are assumed to be lazy, less conscientious, less competent, sloppy, disagreeable, to lack self-discipline, and emotionally unstable. All these reasons can equally explain wage discrimination as well as promotion, hiring and termination of job. Unfortunately, to our knowledge no laboratory study or other empirical analyses exists that may explain why discrimination may change across the wage distribution. This may partly due to the fact that no one has ever thought about the possibility that discrimination exists only at certain levels of the wage distribution. In this sense, our work could be a valid starting point for new research in this field.

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Appendix A

[32] In order to test this hypothesis we should have focused more on the role of starting wages as in Neumark (1999, p. 415), where the author clearly states that "starting wages can potentially reflect either of the two types of discrimination – taste discrimination and statistical discrimination – in a fairly simple way, and an analysis of starting wages leads to some straightforward tests of these alternative models of discrimination".

Table A.1
Sample Selection from full ECHP sample, 1998–2001

Panel A: Sample size for OLS and QR		Panel B: Sample size for IVQR	
298,966	Initial sample, 1998–2001	298,966	Initial sample, 1998–2001
291,162	Observations (90,539 individuals)	291,162	Observations (90,539 individuals)
	7804 Observations dropped with valid BMI in the initial sample		7804 Observations dropped with valid BMI in the initial sample
290,780	Selection for BMI between 15 and 50	290,780	Selection for BMI between 15 and 50
	167 Observations dropped BMI < 15		167 Observations dropped BMI < 15
	215 Observations dropped BMI > 50		215 Observations dropped BMI > 50
287,169	Selection for no pregnant women	287,169	Selection for no pregnant women
	3611 Observations dropped		3611 Observations dropped
		115,995	Selection for construction of sample with biological BMI
			171,174 Observations dropped for
			a. Respondent living alone (37,348)
			b. Respondent living alone in couple without children or in a couple with children aged < 17 (122,768)
			c. Respondent for which was not possible to calculate the BMI because of one of the following relations with the other household components (2728):
			c1. Step/adopted/foster child
			c2. Step/adopted/foster siblings
			c3. Son/daughter in law
			c4. Not related
			d. Respondent for which was not possible to calculate the BMI because of missing information about the relation (8330)
217,248	Selection for sample aged 25–64	89,949	Selection for sample aged 25–64
	16,718 Observations dropped < 25		7316 Observations dropped < 25
	53,203 Observations dropped > 64		18,730 Observations dropped > 64
117,199	Selection for no part-time	46,387	Selection for no part-time
	100,049 Observations dropped		43,562 Observations dropped
87,003	Selection for sample without outliers in the log hourly wage	31,630	Selections for sample without outliers in the log hourly wage
	29,639 Observations dropped (log hourly wage < 1st percentile)		14,751 Observations dropped (log hourly wage < 1st percentile)
	557 Observations dropped (log hourly wage < 99th percentile)		6 Observations dropped (log hourly wage > 99th percentile)
77,687	Selection for sample with no missing data in the covariates	30,100	Selection for sample with no missing data in the covariates
	9316 Observations dropped		1530 Observations dropped
30,313	Final sub-sample women	10,792	Final sub-sample women
47,374	Final sub-sample men	19,308	Final sub-sample men

Table A.2
Descriptive statistics, pooled sample

	Unrestricted sample				Restricted sample			
	Women		Men		Women		Men	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log hourly wage	1.85	0.46	1.99	0.44	1.79	0.55	1.92	0.54
BMI	23.73	3.91	25.75	3.35	23.76	4.06	25.76	3.26
bBMI	–	–	–	–	24.72	3.23	24.53	3.29
Height	163.68	6.45	175.01	7.53	163.1	6.45	174.15	7.42
Weight	63.53	10.7	78.92	11.65	63.10	10.54	78.14	11.13
Sickness	1.26	4.52	0.77	3.36	1.05	4.10	0.75	3.35
Training	0.42	0.49	0.39	0.49	0.33	0.47	0.31	0.46
Private	0.57	0.5	0.7	0.46	0.59	0.49	0.71	0.45
Insurance	0.34	0.47	0.37	0.48	0.26	0.44	0.32	0.47
Age	39.3	9.49	40.47	9.68	38.48	9.23	40.49	9.87
Couple	0.69	0.46	0.74	0.44	0.72	0.45	0.78	0.41
Children	0.34	0.47	0.36	0.48	0.36	0.48	0.39	0.49
Primary	0.31	0.46	0.39	0.49	0.35	0.48	0.45	0.5
Secondary	0.38	0.49	0.38	0.49	0.36	0.48	0.35	0.48
Tertiary	0.31	0.46	0.23	0.42	0.28	0.45	0.21	0.4
Bad health	0.03	0.18	0.03	0.18	0.03	0.18	0.03	0.16
Smoker	0.24	0.43	0.38	0.48	0.24	0.43	0.4	0.49
Professionals	0.36	0.48	0.28	0.45	0.31	0.46	0.24	0.43
Clerks	0.37	0.48	0.19	0.39	0.38	0.48	0.2	0.4
AgrFishery	0.07	0.25	0.25	0.43	0.08	0.28	0.25	0.43
Elementary	0.15	0.36	0.22	0.42	0.18	0.39	0.24	0.43
Agriculture	0.01	0.12	0.03	0.16	0.02	0.14	0.03	0.18
Industry	0.17	0.38	0.38	0.49	0.20	0.40	0.41	0.49
Services	0.70	0.46	0.50	0.50	0.73	0.45	0.51	0.50
Obs.	30,313		47,374		10,792		19,308	

Table A.3
Descriptive statistics by country, unrestricted sample

	Austria				Belgium				Denmark				Finland				Greece			
	Women		Men		Women		Men		Women		Men		Women		Men		Women		Men	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log hourly wage	1.94	0.32	2.11	0.3	2.06	0.28	2.15	0.30	2.16	0.22	2.24	0.26	1.83	0.28	1.97	0.31	1.7	0.44	1.85	0.43
BMI	23.47	3.74	25.65	3.32	23.09	3.7	25.48	3.81	24.4	3.95	25.56	3.4	24.58	4.14	25.95	3.65	23.73	3.57	26.09	3.07
Height	166.45	6.05	177.5	7.09	165.63	6.18	177.39	7.03	166.91	5.91	179.9	6.86	164.72	6.31	178.03	6.6	164.98	5.38	175.96	6.67
Weight	65.03	11.02	80.88	11.82	63.33	10.53	80.24	13.15	68.01	11.68	82.74	12.03	66.68	11.66	82.38	13.37	64.55	9.84	80.76	10.2
Sickness	0.91	3.44	0.8	3.2	1.68	5.35	1.18	4.32	1.73	4.67	0.84	2.91	1.98	5.53	1.06	3.67	0.67	3.03	0.56	2.32
Training	0.57	0.49	0.59	0.49	0.62	0.48	0.61	0.49	0.89	0.32	0.83	0.38	0.79	0.4	0.73	0.45	0.13	0.34	0.17	0.37
Private Sector	0.64	0.48	0.74	0.44	0.33	0.47	0.39	0.49	0.41	0.49	0.73	0.44	0.47	0.5	0.71	0.45	0.59	0.49	0.62	0.49
Insurance	0.2	0.4	0.24	0.43	0.48	0.5	0.58	0.49	0.19	0.39	0.2	0.4	0.86	0.35	0.85	0.35	0.32	0.47	0.37	0.48
Age	38.93	9.17	40	9.22	38.08	8.83	40.64	9.17	41.45	9.64	42.19	10.07	42.56	9.23	41.24	9.3	37.95	8.63	40.89	9.85
Couple	0.6	0.49	0.71	0.46	0.72	0.45	0.8	0.4	0.88	0.32	0.87	0.34	0.76	0.43	0.78	0.41	0.68	0.47	0.72	0.45
Children	0.2	0.4	0.36	0.48	0.33	0.47	0.32	0.47	0.41	0.49	0.37	0.48	0.34	0.47	0.36	0.48	0.36	0.48	0.35	0.48
Primary	0.22	0.41	0.12	0.32	0.12	0.32	0.24	0.43	0.12	0.32	0.15	0.35	0.17	0.38	0.18	0.39	0.23	0.42	0.32	0.47
Secondary	0.67	0.47	0.8	0.4	0.31	0.46	0.36	0.48	0.53	0.5	0.54	0.5	0.37	0.48	0.46	0.5	0.42	0.49	0.38	0.48
Tertiary	0.12	0.32	0.08	0.28	0.57	0.5	0.41	0.49	0.35	0.48	0.31	0.46	0.46	0.5	0.36	0.48	0.34	0.47	0.3	0.46
Bad health	0.02	0.14	0.02	0.12	0.02	0.13	0.02	0.12	0.01	0.11	0.01	0.11	0.04	0.21	0.11	0.31	0.01	0.11	0.01	0.09
Smoker	0.28	0.45	0.39	0.49	0.21	0.41	0.3	0.46	0.33	0.47	0.37	0.48	0.2	0.4	0.3	0.46	0.34	0.47	0.55	0.5
Professionals	0.32	0.46	0.31	0.46	0.25	0.43	0.23	0.42	0.5	0.5	0.46	0.5	0.49	0.5	0.44	0.5	0.34	0.48	0.28	0.45
Clerks	0.5	0.5	0.2	0.4	0.25	0.43	0.11	0.32	0.37	0.48	0.11	0.31	0.33	0.47	0.09	0.29	0.43	0.49	0.25	0.44
AgrFishery	0.05	0.21	0.3	0.46	0.01	0.09	0.08	0.27	0.01	0.11	0.2	0.4	0.04	0.19	0.23	0.42	0.08	0.27	0.23	0.42
Elementary	0.14	0.35	0.19	0.39	0.06	0.23	0.12	0.32	0.09	0.29	0.21	0.4	0.08	0.26	0.17	0.38	0.14	0.35	0.21	0.41
Agriculture	0	0.06	0.01	0.11	0	0.05	0	0.07	0.01	0.09	0.03	0.16	0.01	0.08	0.02	0.12	0.01	0.1	0.01	0.09
Industry	0.19	0.4	0.46	0.5	0.09	0.28	0.21	0.41	0.11	0.31	0.3	0.46	0.09	0.29	0.29	0.45	0.17	0.38	0.32	0.47
Services	0.8	0.4	0.52	0.5	0.47	0.5	0.34	0.47	0.71	0.45	0.48	0.5	0.48	0.5	0.32	0.47	0.81	0.39	0.66	0.47
OBS.	2104		4466		2371		3838		2979		3722		4623		4731		2615		4473	

	Ireland				Italy				Portugal				Spain			
	Women		Men		Women		Men		Women		Men		Women		Men	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log hourly wage	2.09	0.4	2.25	0.39	1.96	0.38	2.03	0.35	1.46	0.56	1.57	0.5	1.94	0.49	2.04	0.45
BMI	23.84	3.81	25.65	3.39	22.74	3.41	25.29	3.05	24.42	4.35	25.85	3.18	23.06	3.58	26.2	3.48
Height	164.13	6.71	176.58	7.23	162.63	6.48	173.77	7.09	160.56	5.85	169.99	6.48	162.42	6.1	172.95	7.2
Weight	64.11	10.16	80.01	11.74	60.07	8.97	76.35	10.04	62.82	10.6	74.7	10.09	60.75	9.38	78.38	11.38
Sickness	1.01	4.06	0.43	2.28	1.13	4.16	0.63	2.9	1.15	4.8	0.83	4	1.01	4.29	0.74	3.66
Training	0.37	0.48	0.35	0.48	0.19	0.4	0.18	0.39	0.19	0.39	0.19	0.39	0.39	0.49	0.3	0.46
Private Sector	0.65	0.48	0.69	0.46	0.53	0.5	0.67	0.47	0.72	0.45	0.82	0.38	0.66	0.47	0.8	0.4
Insurance	0.12	0.33	0.22	0.41	0.18	0.39	0.24	0.43	0.18	0.38	0.24	0.43	0.44	0.5	0.46	0.5
Age	37.19	9.33	39.65	9.91	39.64	9.53	40.8	9.58	38.38	9.75	39.38	9.98	37.81	9.22	40.13	9.71
Couple	0.52	0.5	0.7	0.46	0.68	0.47	0.73	0.45	0.71	0.45	0.74	0.44	0.56	0.5	0.71	0.46
Children	0.36	0.48	0.41	0.49	0.34	0.47	0.38	0.49	0.41	0.49	0.38	0.49	0.28	0.45	0.35	0.48
Primary	0.27	0.44	0.36	0.48	0.3	0.46	0.46	0.5	0.64	0.48	0.74	0.44	0.3	0.46	0.51	0.5
Secondary	0.43	0.5	0.42	0.49	0.54	0.5	0.42	0.49	0.15	0.36	0.13	0.34	0.21	0.41	0.19	0.39
Tertiary	0.3	0.46	0.22	0.41	0.16	0.36	0.12	0.32	0.21	0.4	0.13	0.33	0.49	0.5	0.3	0.46
Bad health	0.01	0.08	0	0.06	0.04	0.19	0.03	0.17	0.07	0.26	0.06	0.23	0.02	0.14	0.02	0.14
Smoker	0.28	0.45	0.28	0.45	0.23	0.42	0.35	0.48	0.13	0.34	0.37	0.48	0.32	0.47	0.43	0.5
Professionals	0.38	0.49	0.35	0.48	0.32	0.47	0.21	0.4	0.24	0.43	0.18	0.39	0.41	0.49	0.27	0.44

Table A.3 (*Continued*)

	Ireland				Italy				Portugal				Spain			
	Women		Men		Women		Men		Women		Men		Women		Men	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Clerks	0.42	0.49	0.17	0.38	0.42	0.49	0.28	0.45	0.33	0.47	0.18	0.39	0.35	0.48	0.16	0.37
AgrFishery	0.02	0.14	0.18	0.38	0.09	0.28	0.23	0.42	0.14	0.35	0.34	0.47	0.05	0.21	0.3	0.46
Elementary	0.18	0.38	0.28	0.45	0.13	0.34	0.22	0.42	0.28	0.45	0.28	0.45	0.19	0.39	0.26	0.44
Agriculture	0	0.04	0.03	0.16	0.02	0.15	0.04	0.19	0.03	0.17	0.03	0.18	0.02	0.13	0.05	0.21
Industry	0.2	0.4	0.39	0.49	0.19	0.4	0.38	0.49	0.28	0.45	0.49	0.5	0.16	0.36	0.44	0.5
Services	0.8	0.4	0.59	0.49	0.74	0.44	0.55	0.5	0.69	0.46	0.47	0.5	0.83	0.38	0.51	0.5
OBS.	1617		3022		5327		8802		4895		6811		3782		7509	

Table A.4
Quantile regressions

	Women					Men				
	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
Austria										
Obesity	0.030	0.018	−0.021	0.065**	0.050*	0.016	0.039***	0.064***	0.062***	0.074***
Overweight	0.019	0.024	0.005	−0.014	−0.017	0.024*	0.025***	0.035***	0.027**	0.043***
Underweight	0.052	0.059**	0.023	0.015	−0.004	0.521***	0.465***	0.383***	0.249***	0.216***
Insurance	0.036	0.081***	0.090***	0.108***	0.092***	0.086***	0.097***	0.113***	0.115***	0.111***
Training	0.099***	0.084***	0.066***	0.030**	0.025	0.065***	0.068***	0.059***	0.053***	0.048***
Private sector	−0.066***	−0.058***	−0.038***	−0.016	−0.044**	0.006	0.043***	0.046***	0.047***	0.057***
Sickness	−0.047	−0.018	0.031	−0.019	−0.056	−0.098*	−0.039	0.012	−0.128***	−0.127**
Bad health	0.057	0.062*	0.016	0.003	−0.025	−0.095**	−0.061**	−0.118***	−0.032	0.147***
Age	0.035***	0.024***	0.027***	0.017***	0.015**	0.018***	0.014***	0.009***	0.008	0.013**
Age squared	−0.000***	−0.000***	−0.000***	−0.000*	0.000	−0.000**	−0.000***	−0.000*	0.000	0.000
Couple	−0.029	−0.017	−0.003	0.028**	0.030**	0.002	0.002	0.062***	0.026*	0.033*
Children	−0.048*	−0.055***	−0.048***	−0.046***	−0.023	0.012	0.017*	−0.017**	−0.007	−0.007
Secondary	0.035	0.056***	0.052***	0.048***	0.038*	0.068***	0.082***	0.087***	0.084***	0.122***
Tertiary	0.101**	0.115***	0.124***	0.068**	0.039	0.147***	0.192***	0.199***	0.287***	0.413***
Smoker	0.039*	0.014	0.020*	0.005	0.001	−0.063***	−0.038***	−0.021***	−0.029**	−0.028**
Clerks	−0.130***	−0.141***	−0.166***	−0.236***	−0.245***	−0.185***	−0.170***	−0.194***	−0.133***	−0.130***
AgrFishery	−0.243***	−0.296***	−0.362***	−0.531***	−0.560***	−0.155***	−0.177***	−0.215***	−0.221***	−0.216***
Elementary	−0.321***	−0.335***	−0.350***	−0.484***	−0.518***	−0.253***	−0.276***	−0.294***	−0.288***	−0.311***
Agriculture	0.049	0.036	0.017	0.031	0.013	−0.086*	−0.038	−0.054**	−0.049	−0.109
Industry	0.038	0.075***	0.083***	0.081***	0.076***	0.067***	0.051***	0.034***	0.039***	0.034**
Constant	0.921***	1.218***	1.329***	1.670***	1.753***	1.326***	1.443***	1.662***	1.792***	1.705***
OBS.			2104					4466		
Belgium										
Obesity	−0.01	−0.034	−0.067**	−0.013	0.001	0.051**	0.039**	0.016	−0.018	−0.019
Overweight	0.015	0.001	−0.018	−0.007	−0.031	0.032***	0.01	0.020**	0.005	0.014
Underweight	−0.042	−0.072***	−0.038	−0.001	−0.029	−0.014	−0.110**	0.053	−0.016	−0.019
Insurance	0.059***	0.031***	0.054***	0.070***	0.075***	0.081***	0.061***	0.071***	0.085***	0.071***
Training	0.094***	0.108***	0.082***	0.054***	0.054***	0.082***	0.096***	0.076***	0.059***	0.056***
Private Sector	0.009	0.008	−0.001	−0.003	0.008	0.011	−0.02	−0.017	0.002	−0.002
Sickness	−0.001	−0.011	0.020	0.016	−0.044	−0.087*	−0.021	0.016	0.007	0.003
Bad health	−0.028	−0.082**	−0.109**	−0.021	0.009	−0.020	−0.061	−0.062*	−0.071**	−0.074*
Age	0.039***	0.035***	0.026***	0.035***	0.029***	0.025***	0.029***	0.027***	0.032***	0.037***
Age squared	−0.000***	−0.000***	−0.000**	−0.000***	−0.000**	−0.000**	−0.000***	−0.000***	−0.000***	−0.000***
Couple	−0.010	−0.027**	0.002	−0.015	−0.012	0.082***	0.070***	0.095***	0.115***	0.095***
Children	0.019	0.048***	0.030**	0.036***	0.038**	0.000	0.016	0.008	0.008	0.037***
Secondary	0.048**	0.075***	0.059***	0.058***	0.037	0.037**	0.033**	0.053***	0.067***	0.086***
Tertiary	0.169***	0.165***	0.167***	0.201***	0.187***	0.157***	0.164***	0.200***	0.254***	0.256***
Smoker	−0.022	−0.041***	−0.045***	−0.045***	−0.051***	−0.016	−0.011	0.004	0.001	−0.012
Clerks	−0.066***	−0.085***	−0.109***	−0.095***	−0.103***	−0.067***	−0.089***	−0.087***	−0.058***	−0.075***
AgrFishery	−0.155**	−0.198***	−0.147**	−0.116**	−0.184**	−0.124***	−0.129***	−0.096***	−0.082***	−0.102***
Elementary	−0.159***	−0.189***	−0.178***	−0.186***	−0.197***	−0.103***	−0.082***	−0.081***	−0.045**	−0.066***
Agriculture	−0.007	−0.065	0.149	0.050	−0.036	−0.101**	−0.136	−0.212***	−0.323***	−0.379***
Industry	0.000	0.016	0.002	−0.011	−0.034	0.057***	0.070***	0.037**	−0.002	0.010
Constant	0.832***	0.939***	1.222***	1.152***	1.357***	0.963***	0.995***	1.134***	1.091***	1.057***
OBS.			2371					3838		
Denmark										
Obesity	−0.057***	−0.066***	−0.048***	−0.051***	−0.060***	0.039**	0.027	0.034***	0.037***	0.022
Overweight	0.002	−0.007	−0.016*	−0.008	−0.015	0.019	0.014	0.014**	0.01	0.012
Underweight	−0.069***	−0.023	−0.006	−0.024	−0.039	0.047	−0.008	0.099**	0.05	−0.023
Insurance	0.017**	0.027***	0.025**	0.021*	0.015	0.044***	0.053***	0.036***	0.033***	0.041***
Training	0.047***	0.030***	0.031**	0.049***	0.046***	0.032**	0.039***	0.020**	0.016	0.021
Private sector	0.019***	0.016**	0.040***	0.077***	0.105***	0.040***	0.043***	0.060***	0.079***	0.086***
Sickness	−0.002	−0.015	−0.033	−0.041	−0.001	−0.076	−0.019	−0.099**	−0.125***	−0.056
Bad health	−0.081***	−0.023	−0.041	−0.061	−0.059*	−0.357***	−0.123*	−0.094***	−0.140***	−0.158***
Age	0.012***	0.012***	0.018***	0.028***	0.029***	0.041***	0.029***	0.014***	0.012***	0.008
Age squared	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000*	0.000
Couple	0.067***	0.041***	0.023**	0.001	0.007	0.048***	0.016	0.019*	0.008	−0.008
Children	−0.005	−0.003	0.017*	0.029**	0.022**	0.021	0.027*	0.028***	0.035***	0.053***
Secondary	0.109***	0.106***	0.073***	0.024	0.022	0.074***	0.072***	0.067***	0.086***	0.067***
Tertiary	0.220***	0.206***	0.150***	0.093***	0.087***	0.151***	0.150***	0.146***	0.151***	0.135***
Smoker	−0.016**	−0.017**	−0.015*	−0.017*	−0.012	−0.048***	−0.034***	−0.022***	−0.009	0.000
Clerks	−0.089***	−0.098***	−0.106***	−0.123***	−0.142***	−0.111***	−0.125***	−0.152***	−0.188***	−0.186***
AgrFishery	−0.073***	−0.063**	−0.046	−0.103**	−0.121***	−0.090***	−0.083***	−0.124***	−0.177***	−0.200***
Elementary	−0.142***	−0.157***	−0.209***	−0.241***	−0.273***	−0.140***	−0.163***	−0.192***	−0.220***	−0.215***
Agriculture	−0.157***	−0.076	−0.141**	−0.185***	−0.138***	−0.094***	−0.118***	−0.094***	−0.012	−0.028
Industry	−0.013	0.013	0.009	−0.025	−0.044***	−0.006	0.001	0.007	0.022**	0.012
Constant	1.459***	1.549***	1.577***	1.503***	1.548***	0.946***	1.270***	1.732***	1.899***	2.054***

Table A.4 (*Continued*)

	Women					Men				
	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
OBS.			2979					3722		
Finland										
Obesity	−0.103***	−0.052***	−0.055***	−0.046***	−0.042**	−0.046***	−0.019	0.005	0.010	0.028
Overweight	−0.044***	−0.040***	−0.035***	−0.032***	−0.013	−0.001	0.006	−0.019*	−0.008	−0.005
Underweight	0.002	−0.011	−0.039	−0.075***	−0.010	−0.362***	−0.177	−0.236***	−0.266***	−0.269**
Insurance	0.122***	0.085***	0.073***	0.066***	0.075***	0.148***	0.111***	0.077***	0.075***	0.047**
Training	0.134***	0.103***	0.082***	0.072***	0.053***	0.072***	0.082***	0.093***	0.098***	0.116***
Private sector	0.001	0.004	0.020**	0.035***	0.053***	0.005	0.006	0.041***	0.035***	0.035**
Sickness	−0.044*	−0.004	−0.004	0.002	−0.016	−0.006	−0.005	−0.017	0.005	0.018
Bad health	−0.005	0.005	−0.016	0.017	0.058**	−0.004	−0.031	−0.007	0.013	0.025
Age	0.033***	0.026***	0.016***	0.017***	0.019***	0.026***	0.028***	0.026***	0.026***	0.036***
Age squared	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
Couple	−0.002	−0.022***	−0.017*	−0.018*	−0.024*	0.062***	0.039**	0.043***	0.023	0.022
Children	−0.01	−0.002	−0.003	0.003	0.012	0.048***	0.037**	0.011	0.009	0.007
Secondary	0.034**	0.025***	0.015	0.003	0.009	0.060***	0.047***	0.034**	0.037**	0.053**
Tertiary	0.130***	0.132***	0.127***	0.167***	0.206***	0.160***	0.151***	0.166***	0.189***	0.208***
Smoker	0.000	0.000	−0.003	−0.013	−0.012	−0.019*	−0.014	−0.034***	−0.033***	−0.042***
Clerks	−0.091***	−0.090***	−0.109***	−0.133***	−0.130***	−0.125***	−0.119***	−0.148***	−0.177***	−0.174***
AgrFishery	−0.175***	−0.141***	−0.153***	−0.138***	−0.184***	−0.070***	−0.091***	−0.120***	−0.124***	−0.130***
Elementary	−0.132***	−0.160***	−0.200***	−0.216***	−0.226***	−0.122***	−0.132***	−0.148***	−0.126***	−0.091***
Agriculture	−0.080**	0.011	−0.003	−0.029	−0.010	−0.025	−0.086*	−0.034	−0.093**	−0.100**
Industry	0.017	0.020*	0.011	0.034**	0.042**	0.017	0.022	0.015	0.017	0.026
Constant	0.667***	0.910***	1.253***	1.366***	1.363***	0.764***	0.880***	1.080***	1.203***	1.077***
OBS.			4623					4731		
Greece										
Obesity	−0.029	−0.042	−0.057**	−0.005	−0.006	−0.044*	−0.059***	−0.019	−0.001	0.000
Overweight	−0.003	0.014	0.001	0.000	−0.014	0.006	−0.001	0.018	0.034***	0.053***
Underweight	0.016	0.024	−0.018	−0.045	0.000	−0.311***	−0.311***	0.023	0.010	0.241***
Insurance	−0.040**	−0.023*	−0.022*	−0.004	−0.010	0.031*	0.034**	0.026**	0.004	−0.004
Training	0.002	0.026	0.052***	0.033**	0.083***	0.109***	0.093***	0.096***	0.117***	0.114***
Private sector	−0.243***	−0.247***	−0.242***	−0.244***	−0.216***	−0.219***	−0.189***	−0.130***	−0.091***	−0.071***
Sickness	0.038	−0.021	0.100*	−0.024	−0.070	−0.176**	−0.035	−0.049	−0.011	−0.116
Bad health	−0.214***	−0.206***	−0.173***	−0.168***	−0.174***	−0.227***	−0.148**	−0.160**	−0.046	−0.061
Age	0.063***	0.066***	0.056***	0.066***	0.061***	0.045***	0.054***	0.060***	0.065***	0.067***
Age squared	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.000***	−0.000***	−0.001***	−0.001***	−0.001***
Couple	0.056***	0.026	0.029**	0.004	0.013	0.108***	0.106***	0.068***	0.046**	0.038
Children	0.047**	0.054***	0.053***	0.043***	0.032*	0.042**	0.052***	0.070***	0.098***	0.080***
Secondary	0.165***	0.176***	0.145***	0.135***	0.165***	0.143***	0.145***	0.165***	0.150***	0.140***
Tertiary	0.346***	0.376***	0.414***	0.481***	0.514***	0.225***	0.216***	0.287***	0.335***	0.332***
Smoker	−0.002	−0.022	−0.012	0.009	−0.001	−0.001	−0.017	−0.016	0.003	0.006
Clerks	−0.092***	−0.083***	−0.140***	−0.193***	−0.230***	−0.148***	−0.176***	−0.179***	−0.238***	−0.276***
AgrFishery	−0.260***	−0.208***	−0.231***	−0.339***	−0.373***	−0.221***	−0.238***	−0.257***	−0.292***	−0.352***
Elementary	−0.278***	−0.260***	−0.281***	−0.285***	−0.315***	−0.182***	−0.213***	−0.220***	−0.254***	−0.293***
Agriculture	−0.131**	−0.144***	−0.110**	−0.058	−0.033	−0.237***	−0.163***	−0.150***	−0.134***	−0.160**
Industry	0.113***	0.080***	0.060***	0.065***	0.050**	0.108***	0.053***	0.044***	0.030*	0.045*
Constant	−0.025	−0.009	0.396***	0.407***	0.561***	0.352***	0.295**	0.262**	0.324***	0.405**
OBS.			2615					4473		
Ireland										
Obesity	−0.064**	−0.046*	−0.035**	0.004	−0.011	−0.002	0.014	0.023	0.038	0.058***
Overweight	−0.047**	−0.007	0.016*	0.037	0.022	0.020	0.012	0.014	0.004	0.022**
Underweight	0.055	0.021	0.016	0.094	0.119	0.089	−0.005	−0.131*	−0.319***	−0.350***
Insurance	0.074***	0.015	−0.003	−0.045	−0.036	0.024	0.040	0.073***	0.071***	0.083***
Training	0.048***	0.073***	0.079***	0.080***	0.075***	0.086***	0.077***	0.040***	0.010	0.024*
Private sector	−0.208***	−0.222***	−0.222***	−0.247***	−0.261***	−0.258***	−0.244***	−0.200***	−0.192***	−0.163***
Sickness	−0.146***	−0.121***	−0.115***	−0.104	−0.151**	−0.128*	−0.143	−0.210***	−0.124*	−0.130***
Bad health	0.035	−0.050	0.151***	0.116	0.059	0.028	0.059	−0.027	0.025	−0.051
Age	0.022***	0.031***	0.035***	0.022**	0.013	0.028***	0.024**	0.017***	0.027***	0.026***
Age squared	−0.000***	−0.000***	−0.000***	−0.000*	0.000	−0.000***	−0.000**	−0.000***	−0.000***	−0.000***
Couple	−0.028	−0.042***	−0.037***	−0.016	−0.007	0.162***	0.138***	0.156***	0.079***	0.102***
Children	0.001	0.023	0.059***	0.067***	0.091***	−0.014	−0.016	0.002	0.020	0.026**
Secondary	0.121***	0.167***	0.168***	0.134***	0.145***	0.087***	0.083***	0.081***	0.121***	0.139***
Tertiary	0.254***	0.305***	0.295***	0.288***	0.295***	0.235***	0.243***	0.295***	0.329***	0.344***
Smoker	−0.006	0.011	−0.040***	0.000	−0.002	−0.044**	−0.034	−0.032***	−0.013	0.006
Clerks	−0.222***	−0.234***	−0.250***	−0.310***	−0.326***	−0.144***	−0.164***	−0.166***	−0.157***	−0.160***
AgrFishery	−0.164***	−0.162***	−0.205***	−0.372***	−0.453***	−0.156***	−0.178***	−0.165***	−0.163***	−0.160***
Elementary	−0.218***	−0.245***	−0.294***	−0.417***	−0.445***	−0.221***	−0.245***	−0.258***	−0.244***	−0.263***
Agriculture	−0.250***	−0.334***	0.023	−0.067	−0.004	−0.515***	−0.370***	−0.074**	0.003	−0.058**
Industry	0.034	0.065***	0.055***	0.114***	0.117***	0.139***	0.145***	0.131***	0.131***	0.121***
Constant	1.511***	1.365***	1.410***	1.867***	2.127***	1.258***	1.481***	1.745***	1.681***	1.681***

Table A.4 (*Continued*)

	Women					Men				
	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
OBS.			1617					3022		
Italy										
Obesity	−0.065**	−0.056**	−0.030	−0.050**	−0.080***	−0.062***	−0.055***	−0.033***	−0.030**	−0.021
Overweight	−0.032***	−0.026**	−0.024***	−0.043***	−0.044***	0.014*	0.014*	0.013**	0.018**	0.024**
Underweight	−0.051**	−0.026	−0.024	−0.045**	−0.041**	−0.233***	−0.220***	−0.192***	−0.136**	−0.143*
Insurance	−0.026**	−0.027***	−0.011	−0.002	0.027**	0.003	0.012	0.018**	0.013	0.023**
Training	0.115***	0.090***	0.099***	0.111***	0.082***	0.112***	0.104***	0.084***	0.083***	0.067***
Private sector	−0.128***	−0.117***	−0.094***	−0.047***	−0.036***	−0.060***	−0.057***	−0.032***	−0.006	0.021*
Sickness	−0.034	−0.019	−0.025	−0.046	−0.029	−0.012	−0.043	−0.060*	−0.071**	0.008
Bad health	0.103***	0.069***	0.074***	0.057**	0.046*	−0.065***	−0.057**	−0.094***	−0.076***	−0.048*
Age	0.050***	0.031***	0.028***	0.025***	0.019***	0.051***	0.047***	0.029***	0.023***	0.019***
Age squared	−0.001***	−0.000***	−0.000***	−0.000***	−0.000**	−0.001***	−0.000***	−0.000***	−0.000***	−0.000**
Couple	0.002	0.007	−0.001	−0.014	−0.010	0.045***	0.044***	0.073***	0.090***	0.098***
Children	0.018	0.015	0.038***	0.046***	0.047***	0.028**	0.027***	0.038***	0.042***	0.044***
Secondary	0.196***	0.140***	0.121***	0.119***	0.105***	0.114***	0.100***	0.083***	0.100***	0.113***
Tertiary	0.295***	0.248***	0.299***	0.455***	0.456***	0.230***	0.243***	0.300***	0.446***	0.496***
Smoker	0.014	0.011	0.014*	0.022**	0.023**	−0.030***	−0.028***	−0.010	0.006	0.016
Clerks	−0.043***	−0.078***	−0.130***	−0.242***	−0.281***	−0.045***	−0.076***	−0.110***	−0.114***	−0.128***
AgrFishery	−0.121***	−0.157***	−0.201***	−0.318***	−0.357***	−0.105***	−0.108***	−0.173***	−0.231***	−0.250***
Elementary	−0.112***	−0.133***	−0.194***	−0.337***	−0.406***	−0.108***	−0.121***	−0.162***	−0.197***	−0.215***
Agriculture	−0.382***	−0.400***	−0.265***	−0.017	0.000	−0.269***	−0.211***	−0.167***	−0.087***	−0.111***
Industry	0.070***	0.049***	0.029**	0.020	0.017	0.054***	0.043***	0.024***	0.018*	−0.002
Constant	0.470***	1.007***	1.249***	1.482***	1.697***	0.523***	0.709***	1.236***	1.476***	1.623***
OBS.			5327					8802		
Portugal										
Obesity	0.007	0.002	−0.038*	−0.031	−0.034	−0.062***	0.025	0.028*	0.039	0.036
Overweight	−0.016	−0.025**	−0.023**	−0.019	−0.037**	0.017	0.031**	0.018*	0.030**	0.039**
Underweight	0.104***	0.105***	0.003	0.001	0.002	0.159*	0.097	−0.058	0.020	0.049
Insurance	0.026*	0.037**	0.022	0.030**	0.066***	0.035**	0.063***	0.087***	0.100***	0.130***
Training	0.087***	0.102***	0.147***	0.133***	0.104***	0.137***	0.141***	0.141***	0.134***	0.128***
Private sector	−0.288***	−0.287***	−0.223***	−0.160***	−0.146***	−0.103***	−0.063***	−0.051***	−0.013	−0.007
Sickness	−0.043	0.046	0.006	0.014	0.017	0.057	−0.012	−0.022	0.024	−0.032
Bad health	−0.015	−0.019	−0.050**	−0.072***	−0.090***	−0.132***	−0.118***	−0.116***	−0.121***	−0.160***
Age	0.011**	0.011***	0.013***	0.019***	0.023***	0.029***	0.031***	0.033***	0.043***	0.036***
Age squared	−0.000*	−0.000*	0.000	−0.000*	−0.000*	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
Couple	0.091***	0.063***	0.059***	0.042***	−0.023	0.079***	0.099***	0.113***	0.141***	0.151***
Children	0.015	0.012	−0.019	−0.026**	0.003	0.030**	0.022	0.035***	0.026	0.031
Secondary	0.123***	0.161***	0.252***	0.337***	0.334***	0.124***	0.127***	0.242***	0.222***	0.211***
Tertiary	0.594***	0.558***	0.652***	0.654***	0.634***	0.540***	0.646***	0.637***	0.652***	0.608***
Smoker	0.067***	0.074***	0.113***	0.134***	0.075***	−0.026**	−0.017	−0.035***	−0.023*	0.004
Clerks	−0.218***	−0.257***	−0.279***	−0.280***	−0.318***	−0.236***	−0.224***	−0.251***	−0.208***	−0.234***
AgrFishery	−0.273***	−0.350***	−0.407***	−0.557***	−0.611***	−0.246***	−0.228***	−0.310***	−0.329***	−0.371***
Elementary	−0.286***	−0.354***	−0.397***	−0.486***	−0.500***	−0.313***	−0.281***	−0.342***	−0.353***	−0.403***
Agriculture	−0.020	0.022	−0.059**	−0.083**	−0.135***	−0.335***	−0.285***	−0.218***	−0.089**	−0.161***
Industry	0.115***	0.103***	0.060***	0.097***	0.054**	0.077***	0.027*	−0.022*	−0.052***	−0.062***
Constant	0.973***	1.106***	1.197***	1.196***	1.246***	0.610***	0.615***	0.761***	0.714***	0.978***
OBS.			4895					6811		
Spain										
Obesity	−0.117***	−0.116***	−0.096***	−0.113***	−0.105***	−0.011	−0.039**	−0.021	−0.016	−0.001
Overweight	0.000	−0.001	−0.010	−0.013	−0.033	0.011	0.015	−0.008	0.015	0.008
Underweight	−0.071	−0.044	−0.006	0.050*	0.051	−0.147**	−0.249**	−0.063	0.045	0.062
Private sector	−0.184***	−0.196***	−0.167***	−0.143***	−0.122***	−0.191***	−0.148***	−0.061***	0.016	0.042***
Insurance	0.13ß2***	0.098***	0.066***	0.057***	0.048***	0.056***	0.061***	0.064***	0.060***	0.063***
Training	0.123***	0.124***	0.111***	0.100***	0.100***	0.145***	0.147***	0.156***	0.147***	0.114***
Sickness	0.088	0.045	−0.030	−0.016	−0.034	−0.211***	−0.212***	−0.060	−0.035	−0.038
Bad health	0.016	0.021	0.007	0.033	0.007	−0.065	−0.088**	−0.144***	−0.195***	−0.193***
Age	0.063***	0.057***	0.054***	0.050***	0.054***	0.030***	0.027***	0.023***	0.024***	0.031***
Age squared	−0.001***	−0.001***	−0.001***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000**	−0.000*	−0.000***
Couple	0.060***	0.058***	0.049***	0.033***	0.051***	0.067***	0.069***	0.064***	0.065***	0.073***
Children	0.081***	0.019	0.030*	0.016	−0.007	0.012	0.029**	0.027**	0.033*	0.037***
Secondary	0.130***	0.136***	0.145***	0.154***	0.156***	0.116***	0.115***	0.103***	0.125***	0.154***
Tertiary	0.237***	0.244***	0.250***	0.262***	0.223***	0.195***	0.189***	0.215***	0.241***	0.250***
Smoker	0.005	0.022	0.042***	0.046***	0.038**	−0.050***	−0.041***	−0.023**	−0.032*	−0.034***
Clerks	−0.265***	−0.291***	−0.324***	−0.358***	−0.355***	−0.188***	−0.193***	−0.261***	−0.247***	−0.213***
AgrFishery	−0.346***	−0.406***	−0.484***	−0.563***	−0.525***	−0.215***	−0.233***	−0.318***	−0.340***	−0.321***
Elementary	−0.337***	−0.368***	−0.387***	−0.461***	−0.488***	−0.263***	−0.291***	−0.376***	−0.375***	−0.374***
Agriculture	−0.099	−0.097	−0.172***	−0.096**	−0.093	−0.253***	−0.216***	−0.209***	−0.203***	−0.212***
Industry	0.116***	0.102***	0.117***	0.132***	0.092***	0.158***	0.130***	0.093***	0.062***	0.039***
Constant	0.093	0.393**	0.641***	0.880***	0.911***	0.903***	1.064***	1.341***	1.447***	1.383***

Table A.4 (*Continued*)

	Women					Men				
	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)	α(15th)	α(25th)	α(50th)	α(75th)	α(85th)
OBS.			3782					7509		

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table A.5
Trade union density, bargaining governability and EPL

	Union density (%)	Bargaining governability	EPL strictness
Austria	37	3	2.3
Belgium	56	1	2.5
Denmark	74	4	1.5
Finland	76	4	2.1
Greece	27	(a)	3.5
Ireland	38	1	1.1
Italy	35	1	3.4
Portugal	24	3	3.7
Spain	15	3	3.1

Notes: Trade union density is defined as the proportion of the labor force belonging to a trade union (for details see OECD, 2004). Bargaining governability is an indicator of vertical co-ordination and is a measure of the extent to which collective contracts are effectively followed at lower levels. This indicator assumes the following values: 4 when collective agreement are legally enforceable and there is an automatic peace obligation during the validity of the agreement; 3 when collective agreement are legally enforceable and there are widespread but optional peace of obligation clauses in agreements; 2 when there is legal enforceability, but no effective tradition or practice of peace of obligation clauses; 1 when neither of the above conditions are effectively present. For further detail on bargaining governability, see OECD (2004) and Traxler et al. (2001). The EPL is a summary indicator, obtained as weighted average of three main components: protection against individual dismissal of a regular employee, protection against individual dismissal of a temporary employee and protection against collective dismissals. For further details on EPL see OECD (1999).

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