Fat Chance! Obesity and the Transition from Unemployment to Employment

Marco Caliendo*
IZA, Bonn

Wang-Sheng Lee†
RMIT University

November 10, 2010

Abstract

Based on two waves of survey data from the IZA Evaluation dataset - a unique panel data set that collects extensive information on a sample of newly unemployed persons in Germany in 2007-2008 - this paper estimates differences in job search behaviour and labor market outcomes between obese/overweight and healthy weight persons. In this paper, we have a rich set of conditioning covariates, including measures that control for education, demographic characteristics, labor market history, psychological factors, cognitive skills and health, and have access to panel data to ensure that we are measuring the effects of past obesity on future employment states. As such, any residual differences between otherwise similar obese and non-obese individuals, in terms of how quickly they get reattached to the labor market, is likely to be due to some form of discrimination by employers against the obese. Estimates of weight discrimination are provided separately for men and women.

JEL Classification: I10, I12, J21, J23

Key words: Obesity, discrimination, employment, labor demand

* IZA, P.O. Box 7240, 53072 Bonn, Germany, E-mail: caliendo@iza.org

† RMIT University, Level 12, 239 Bourke Street, Victoria 3000, Australia. Email: wangsheng.lee@rmit.edu.au

1. INTRODUCTION

At present, there exist widespread anti-discrimination laws against race, gender and disability in many countries around the world. In part, this might be attributed to the fact that hundreds of studies have in the past documented inequitable outcomes associated with race, gender and disability after controlling for a host of socio-demographic characteristics. Textbooks in labor economics routinely include chapters explaining how decomposition techniques can be useful in estimating the size of such discrimination. Expert witnesses are often asked to provide testimony in law suits where discrimination has been alleged; often, the standard decomposition technique introduced by Blinder (1973) and Oaxaca (1973) that is widely used in the field of labor economics is the technique employed to provide (or demonstrate the lack of) statistical evidence for discrimination.

Obesity has recently emerged as a prevalent problem in many developed countries. For example, between the periods 1976-1980 and 1999-2000, the prevalence of overweight (BMI ≥ 25) persons in the US increased from 46% to 65%, and the prevalence of obesity (BMI ≥ 30) increased from 15% to 31%. (Flegal *et al.*, 2002).[1] Similarly in Europe, the prevalence of obesity in men ranged from 4.0% to 28.3% and in women from 6.2% to 36.5% during the period 1980-2005. Eastern Europe and the Mediterranean countries showed higher prevalences of obesity than countries in Western and Northern Europe (Berghöfer *et al.*, 2008). The alarming rise of obesity over the years has led to the practice of a new form of discrimination – weight discrimination.

Researchers estimate that at present, weight discrimination is comparable to rates of race and age discrimination, especially among women. In 1995-96, weight discrimination was reported by 7% of US adults. In 2004-2006, that percentage rose to 12% of adults (Andreyeva *et al.*, 2008). Puhl and Brownell (2001) published the first comprehensive review of several decades of research documenting bias and stigma toward overweight and obese persons. Their review summarized weight stigma in domains of employment, health care, and education, demonstrating the vulnerability of obese persons to many forms of unfair treatment. It highlighted that weight discrimination is rampant in the workplace, health care and education arenas. Based on data from the National Survey of Midlife Development in the US, a

[1] Body mass index (BMI) is the ratio of weight measured in kilograms, to squared height measured in meters.

nationally representative sample of adults aged 25–74 years, Roehling *et al.* (2007) found that overweight respondents were 12 times more likely, obese respondents were 37 times more likely, and severely obese respondents were 100 times more likely than normal-weight respondents to report employment discrimination. In addition, women were 16 times more likely to report weight-related employment discrimination than men. A meta-analysis of 32 experimental studies which investigated weight discrimination in employment settings was recently conducted by Roehling *et al.* (2008). Typically, such experimental studies ask participants to evaluate a fictional applicant's qualifications for a job, where his or her weight has been manipulated (through written vignettes, videos, photographs or computer morphing). Outcome variables examined in these studies included hiring recommendations, qualification/suitability ratings, disciplinary decisions, salary assignments, placement decisions, and co-worker ratings. Across studies, it was demonstrated that overweight job applicants and employees were evaluated more negatively and had more negative employment outcomes compared to non-overweight applicants and employees.

Despite such widespread evidence that obese people experience discrimination, to date, with the exception of the state of Michigan in the US, which enacted a law in 1977 prohibiting discrimination against overweight people, there are no laws protecting overweight people from discrimination in employment, education, and health care.

Based on panel data on a sample of newly unemployed obese and non-obese persons in Germany in 2007-2008 who are seeking work, this paper examines the question of whether obese job applicants experience employer discrimination and are less likely than non-obese job applicants to transition from unemployment to employment. In addition to observing the employment outcomes of job applicants, a novel feature of our data set is that we also have information on the search behavior of job applicants. We therefore will be given insights as to whether any observed differences in labor market outcomes have arisen because one group simply was less motivated or tried less hard to look for a job. The rest of this paper is organized as follows. Section 2 discusses the data in more detail. Section 3 provides more background and discusses some theoretical motivations. Section 4 discusses the methods used. The empirical results are provided in Section 5. Finally, Section 6 concludes.

2. DATA

The IZA-Evaluation Dataset is an ongoing data collection process which is specifically designed to shed more light on the transition process from unemployment to employment (see Caliendo *et al*., 2010, for details). It consists of two components, an administrative part as well as an additional survey data set. The sampling is restricted to individuals who are 16 to 54 years old, and who receive or are eligible to receive unemployment benefits under the German Social Code III. The administrative part covers a random inflow sample into unemployment for the years 2001-2008 containing over 920,000 individuals. Administrative records are based on the 'Integrated Labour Market Biographies' of the Institute for Employment Research (IAB), containing relevant register data from four sources: employment history, unemployment support recipience, participation in active labor market programs, and job seeker history. For the complementary survey a random sample of individuals who entered unemployment between June 2007 and May 2008 is chosen. From the monthly unemployment inflows of approximately 206,000 individuals in the administrative records, a 9% random sample is drawn which constitutes the gross sample. Out of this gross sample each month representative samples of approximately 1,450 individuals are interviewed, so that after one year 12 monthly cohorts were gathered. The key feature of the data set is that individuals are interviewed shortly after they become unemployed and are asked a variety of non-standard questions. In addition to measuring an extensive set of individual-level characteristics and labor market outcomes, a particular strength of the survey dataset is that it contains many non-standard, innovative questions including search behavior, social networks, psychological factors, cognitive and non-cognitive skills, subjective assessments on future outcomes, and attitudes. As will be discussed in a later section, such rich micro-level data are important in helping us identify the effects of obesity on labor market outcomes using decomposition and matching approaches.

For the purposes of this paper, we focus on three cohorts of the survey dataset (June 2007, October 2007 and February 2008) in which data on height and weight were collected. For these three cohorts, two waves of data are available and analyzed in this paper. In wave 1, the initial interviews were conducted close to the unemployment entry. Wave 2 was conducted one year after entry into unemployment. Our analysis sample comprises of the 784 men and 673 women who responded to both waves 1 and 2 of the survey; out of these 401 men and 438 women were still unemployed and actively searching for a job in wave 1.

This paper uses body mass index (BMI) as our measure of body size, which is based on self-reported weight in kilograms divided by self-reported height in meters squared. According to widely used classifications by the U.S. National Institutes of Health, an individual who has a BMI below 18.5 is underweight; one whose BMI is between 18.5 and 25 is healthy weight; one whose BMI is between 25 and 30 is overweight; and one whose BMI is over 30 is obese. Table 1 displays the sample sizes of men and women in each of the four BMI categories in our analysis data set. Note that as there are very few individuals with BMI values below 18.5, we omit this group of individuals when performing any further analysis in this paper.

* Table 1 about here *

Table 2 provides some descriptive statistics regarding the socio-demographic characteristics of individuals who are of normal weight, overweight and obese. These descriptive statistics indicate that there are different types of men and women in each of the groups and that naively comparing outcomes across groups will not yield any informative insights. For example, obese men tend to be on average older (38.28 years) than overweight men (36.32 years) or healthy weight men (31.07 years). Similarly, obese women tend to be older than overweight women who are in turn older then healthy weight women too, where the average ages are 40.92, 38.14 and 35.70 respectively. In terms of education, it can be seen that a larger proportion of healthy weight men had technical college or university degrees as compared to obese men (0.24 vs. 0.21). This difference was more pronounced when comparing healthy weight women and obese women (0.32 vs. 0.18).

As can be seen in Table 2, we also control for labor market history using several different measures. Most importantly, we observe the number of months individuals spent in employment and unemployment over their lifetime and later use this information adjusted for age in our regression models. Additionally, we also observe whether individuals receive unemployment benefits and the level of benefits. Since benefits in Germany are directly related to previous net income, this should give us a good approximation also of the unobservable variables potentially influencing employment outcomes. Finally, we also have information on the employment status of the individuals just before they become registered as unemployed, e.g., whether they have been in paid-employment, self-employment, subsidized employment or school.

* Table 2 about here *

Table 3 examines group differences in personality traits, cognitive skills and health. With regards to personality, it can be seen that obese men and women have lower values for their internal locus of control, which suggest that obese persons are more likely to believe that fate or chance primarily determine their life events and destiny. Another main difference that can be seen is with regards to health, where obese men and women are more likely than non-obese men and women to have bad general health and a physical impairment in the last two months. In terms of the two short tests for cognitive skills conducted in the survey, there appear to be no clear cut differences between the three groups of individuals. Whereas overweight men score well in both tests (when compared to obese and healthy weight men), we find that healthy weight women perform better than overweight and obese women.

* Table 3 about here *

3. OBESITY AND LABOR MARKET OUTCOMES

Much research in the economics literature has focused on examining the effects of different types of training programs for disadvantaged individuals on labor market outcomes. For example, Card *et al.* (2009) perform a meta analysis of 97 studies conducted between 1995 and 2007 and find that in general, job search assistance programs have relatively favorable short-run impacts, whereas classroom and on-the-job training programs tend to show better outcomes in the medium-run than the short-run. But how do employers decide whom to hire from a pool of unemployed workers? What factors affect how long they are hired for?

Given the tendency for obesity to be strongly associated with low socioeconomic status (e.g., Brunello *et al*., 2009), the issue of how obesity affects the transition from unemployment to employment and whether there is social stigmatization and discrimination warrants further detailed attention. The program evaluation literature has generally focused on assessing the effectiveness of various types of training that has been provided which affect the supply side of the market; considerable less attention has been placed on the demand side of the market. With the exception of Cawley and Danzinger (2005), we are not aware of any other study that focuses on obesity as a barrier in helping welfare recipients transition from welfare-to-work.

A correlation between body weight and labor market outcomes could arise for several reasons. As Cawley (2004) notes, the first explanation is that obesity lowers wages. This explanation consists of both demand and supply side factors. On the supply side, obesity may impair one's ability to work through having poor health or low self-esteem. In addition, obese persons may be less motivated to invest in their own human capital. For example, obese persons might place a higher premium on present consumption and satisfaction and be less concerned about longer term health consequences. They could therefore also plausibly be less likely to engage in activities like training, which only have payoffs in the more distant future. On the demand side, there could be discrimination by employers. This might arise from employers being prejudiced against the obese and having a distaste for working or dealing with them; from employers stereotyping obese workers and thinking that they are less productive; or having a higher uncertainty or a lack of knowledge about the productivity of obese workers. The second explanation is that low wages or unemployment help cause obesity (i.e., the case of reverse causality). This would be true if poorer people consume cheaper food high in fat content. The third explanation is that there could be unobserved variables that are correlated with both obesity and employment (e.g., individual time preference).

There is a small literature in economics that examines the effects of obesity on employment and wages. Early studies in this literature include Register and Williams (1990) and Loh (1993) who based their studies on the 1982 National Longitudinal Survey of Youth (NLSY). Register and Williams (1990) find that obesity reduces females' wages by 12 percent but has no significant effects for males, whereas Loh (1993) did not find any significant effects of obesity on wage levels for both males and females. Using the 1989 wave of the NLSY, Pagan and Davila (1997) find that obesity reduces female wages but not those of males. Using data from the National Child Development Study (NCDS) to examine the impact of obesity on the labour market outcomes of young British adults, both Sargent and Blanchflower (1994) and

Harper (2000) find using logit models that obesity had an insignificant effect on unemployment for both males and females.

More recent studies in this literature have paid more attention to controlling for the possible endogeneity of obesity with employment and wages. Cawley (2000) addresses the endogeneity between obesity and employment using an instrument variables (IV) regression approach. He analyses the impact of BMI on wages and employment in a sample taken from the NLSY panel over the period 1981 to 1998. Restricting his analysis to females who have borne children, the instruments for BMI he uses are the BMI of a biological child aged six to nine years plus interactions of this with the child's age and gender. He found that BMI had a positive effect on employment (statistically significant at the 10% level). Morris (2007) also estimates IV models to investigate the impact of obesity on employment using a different data set – data on men and women from the Health Survey for England. Morris instruments for individual obesity using the prevalence of obesity in the area in which the respondent lives. In his IV models, he finds that obesity has a statistically significant and negative impact on employment in both males and females. In addition, as an alternative way of controlling for the endogeneity of obesity and employment, Morris also finds using propensity score matching that for males there is a significant and negative impact of obesity on employment.

Several other authors have also attempted to examine the causal effects of obesity on wages. In order to estimate the marginal effect of a change in weight on wages (i.e., estimate weight-wage elasticities), several different econometric approaches have been employed in the literature. Lagged body weight has been used in place of current body weight in order to avoid the influence of wages on contemporaneous weight (e.g., Conley and Glauber, 2006); fixed effects models have been used to eliminate the influence of time-invariant unobserved heterogeneity on weight and wages (e.g., Averett and Korenman, 1996); and IV approaches have also been used (e.g., Cawley, 2004; Brunello and D'Hombres, 2007) where in both cases obesity was instrumented using the BMI of a biological family member. These studies generally tend to find that obese women earn less than healthy-weight women.

As Garcia and Quintana-Domeque (2006) and Cawley (2007) note, establishing convincing causal effects of obesity is not easy. With regards to the use of instruments for obesity using the BMI of a family member, there is a possibility that a substantial part of the genes responsible for obesity are also responsible for other factors that affect labor market success. Using area averages of BMI as an instrument as in Morris (2007) can also be problematic if there is non-random selection into areas where individuals live based on unobservables related to obesity and occupational attainment. Lagged BMI is sometimes also used in a regression to establish a Granger type of causality. However, independence of the lagged BMI variable on the error term is required, which is unlikely to be true. Finally, fixed effects models have been used to eliminate the influence of time-invariant unobserved heterogeneity on weight and wages. But these models require BMI to be strictly exogenous and uncorrelated with the error term for all leads and lags, which is unlikely to be the case. Furthermore, these models eliminate time-invariant variables and are essentially identified by those who change BMI categories.

Experiments provide one convincing way of estimating the causal effects of obesity. Adopting a field experiment approach, Rooth (2009) identifies differences in labor market outcomes due to obesity that can be interpreted as causal. He achieves this by weight manipulation of facial photographs attached to job applications. The basis for conducting such an experiment comes from lab settings in which psychologists and sociologists have been documenting systematic differential treatment by employers against obese applicants (e.g., see Roehling, 1999). In his experiment, Rooth (2009) sent two equivalent applications to advertised job openings with the only difference being that one has a picture of a person with normal weight and the other has a digitally modified picture to make the same person look obese. A key advantage of this approach is that it helps ensure that other supply side characteristics of the job applicant are held constant. However, a disadvantage of field experiments of this nature is that it focuses on callback rates or offers for an interview, and not the actual event of being offered a job.[2]

Given the difficulties in plausibly estimating a causal effect of obesity when an experimental design is not feasible, as an alternative, it is possible to perform an accounting exercise and simply focus on estimating the magnitude of the raw and conditional gap in outcomes between obese and non-obese individuals. In this case, the focus is not on estimating average treatment effects but instead on a more general

[2] In addition to responding to job vacancies using written job applications, approaches using actual persons who pretend to have similar qualifications except for the variable of interest (race, gender etc.) have also been used. The advantages and disadvantages of these ‘audit tests’ are discussed in more detail in Riach and Rich (2002), who provide a broad survey of such field experiments of discrimination.

issue – estimating the magnitude of any potential discrimination that might lead to obese job applicants being treated differently from non-obese applicants. Here, decomposition approaches can be used to distinguish between explained and unexplained components of the gap that is observed between obese and non-obese individuals. For example, using a combination of Swedish data on men that enlisted in the military and administrative tax records, Lundborg *et al.* (2010) obtain a raw obesity earnings gap of about 18 percent. However, by controlling for demographic characteristics and a variety of supply side characteristics such as cognitive skills, non-cognitive skills, measures of physical fitness, they find that the obesity earnings gap is reduced substantially to less than three percent. The authors therefore argue that the negative association between obesity and earnings runs mainly through obesity's association with physical fitness and skills.

Empirically disentangling the demand and supply side factors, or the two way relationship between weight and wages is required if one is interested in estimating the causal effects of obesity on labor market outcomes. However, when one is simply interested in an accounting exercise of estimating the gap in outcomes between obese and non-obese individuals and not in making any causal statements, resolving the endogeneity problem is not a central issue.

3.1 Discrimination against the obese – a theoretical perspective

Employers might choose not to hire obese persons due to widespread negative stereotypes that overweight and obese persons are lazy, unmotivated, lacking in self-discipline, less competent, noncompliant, and sloppy (Puhl and Brownell, 2001). Is there an economic rational basis for such discrimination?

Statistical discrimination is said to occur when rational decision makers use aggregate group characteristics to evaluate individuals with whom they interact. As a result, individuals belonging to different groups may be treated differently even if they share identical observable characteristics in every other respect. The basic premise of statistical discrimination is that firms have limited information about the skills and turnover propensity of applicants, particularly workers with little labor market history. As such, firms have an incentive to use easily observable group characteristics to 'statistically discriminate' among workers if these characteristics are correlated with performance (e.g., Altonji and Blank, 1999).

Several theoretical models of statistical discrimination developed in the economics literature suggest why there could be discrimination by employers against the obese. In his seminal work on discrimination, Becker (1957) assumes that some agents have a ‘taste’ for discrimination. Employers taste for discrimination affects profits through wages and hiring decisions. An implication of Becker’s model is that preferential hiring occurs – employers are less likely to hire obese workers of identical productivity.

Alternatively, information problems are fundamentally important in labor markets. When firms are uncertain about the true abilities and effort levels of prospective employees, it is common to turn to group identification as a signal of underlying productivity. The statistical discrimination model in Aigner and Cain (1977) highlights the type of discrimination that can occur when there is a higher uncertainty about the productivity of obese workers. The model posits two groups of individuals with known normal distributions of productivity. Although the population distribution of productivities is known, the actual productivity of any given worker is unobservable to firms. Instead, firms only observe a noisy signal of productivity, $s = \mu + \varepsilon$ where ε is $N(0,\ \sigma_{\varepsilon}^{2})$. Assuming that the signal is noisier for the obese than the non-obese, and that firms are risk-averse, Aigner and Cain (1977) show that the group with a noisier signal will receive lower average wages. This is because with risk aversion, wages depend not only on the conditional expectation of productivity but also on the conditional variance of productivity. As a result, hiring rates are different across groups even though productivity might be the same.

Theoretical models of discrimination attempt to rationalize discrimination. However, one must also be willing to concede that economic theory cannot fully explain the long run existence of discrimination. As Arrow (1998) notes, “[i]t is natural to suppose that economic analysis can cast light on the economic effects of discrimination. But can a phenomenon whose manifestations are everywhere in the social world really be understood, even in only one aspect, by the tools of a single discipline?” (p. 91). Darity and Mason (1998) also cast a negative light on the ability of economic theory to account for discrimination: “Since Becker's work, orthodox microeconomics has been massaged in various ways to produce stories of how discrimination might sustain itself against pressures of the competitive market. The tacit assumption of these approaches has been to find a way in which discrimination can increase business profits, or to identify conditions where choosing not to discriminate might reduce profits" (p. 82).

3.2 Discrimination against the obese – a practical perspective

In this section, we turn to factors that are outside the scope of economic theory that might help account for discrimination against the obese. Some empirical evidence in the literature suggests that there might be logical reasons why employers choose not to employ the obese. Finkelstein *et al*. (2005) report that obesity results in significant increases in medical expenditures and absenteeism among full-time employees. They estimate that the costs of obesity (excluding overweight persons) at a firm with 1000 employees are approximately US$285,000 per year. Cawley *et al.* (2007) found that obese women were 61 percent more likely to miss work time, compared to women of healthy weight. For morbidly obese women (BMI 40 or higher), the figure rose to 118 percent. For women, obesity was linked to absenteeism across all occupational categories. For men, the relationship varied by occupation. For example, the likelihood of missed work time among men in professional and sales occupations increased along with weight category. In other occupations – including managers, office workers, and equipment operators – the risk of missed work time increased only for morbidly obese men. Taken as a whole, Cawley *et al.* (2007) found that obesity and morbid obesity was associated with increased rates of work absenteeism, with an estimated cost of $4.3 billion (2004 dollars) in the US.

However, the results of these studies need to be interpreted carefully. Due to weight discrimination in health care, overweight patients might be reluctant to seek medical care, be more likely to cancel or delay medical appointments, or put off important preventative health care services. Viewed in this light, higher absenteeism amongst the obese might be the result of discrimination and should not be used to justify discrimination. In section 5, we test to see if health is an important channel by which the effects of obesity operate. We do so by estimating the obesity gap with and without health variables included. If health is an important mediating variable, we expect to see any gap between obese and non-obese persons to become smaller when health variables are controlled for.

4. METHODOLOGY

This paper uses a pooled linear decomposition approach to estimate the gap in labor market outcomes between the obese and healthy weight persons, as well as between overweight and healthy weight persons. As we explain below, the approach we use is closely related to the estimation of average treatment effects. The main difference is that the assumptions we invoke using the decomposition approach are weaker than the assumptions underlying the estimation of causal effects.

4.1 Linear decomposition

A common approach employed in the literature to distinguish between explained and unexplained components is to perform a linear decomposition, based on the seminal papers of Blinder (1973) and Oaxaca (1973). In the standard Blinder-Oaxaca (BO) decomposition, separate regressions are estimated for group A ($Y_i = \beta_A X_i + \varepsilon_i$) and for group B ($Y_i = \beta_B X_i + \varepsilon_i$), where *X* are individual level characteristics that help explain differences in *Y*. The average gap in outcomes ($\overline{Y}_A - \overline{Y}_B$) can be expressed as the sum of two components: $\beta_A(\overline{X}_A - \overline{X}_B) + (\beta_A - \beta_B)\overline{X}_B$. The first part is attributed to differences in average characteristics between the two groups. The second part is due to differences in average returns to the individual characteristics, which may reflect discrimination. $\beta_A \overline{X}_B$ represents the outcome for group B if they were treated as if they were members of group A. It also represents the outcome for members of group A, if they had the average characteristics of members of group B. An equally valid decomposition is to express the components of the gap as: $\beta_B(\overline{X}_A - \overline{X}_B) + (\beta_A - \beta_B)\overline{X}_A$. Many papers acknowledge this by reporting the results of both decompositions, as well the decompositions from a pooled regression without group specific intercepts based on a suggestion by Neumark (1988).

It is worth thinking carefully about what various types of BO decompositions measure precisely. Closely related to the literature on decomposition and the estimation of the size of unexplained gaps is the literature on treatment effects. When performing a decomposition, one controls for as many possible relevant covariates as possible, calling the remaining group difference unexplainable or a gap. Similarly, when estimating causal effects, one also controls for as many relevant covariates as possible in order to make the treatment and control groups as similar as possible. The remaining difference between the groups is then referred to as the average treatment effect. Their close relationship is immediately obvious when one simply substitutes the term ‘treatment effect’ for the term ‘unexplained gap’ in a regression framework.

Developments in the program evaluation literature have been very useful in helping clarify different parameters of interest one might be interested in estimating, and helping spell out what the two equally valid versions of the BO decomposition accomplish. In the first instance when the average gap is expressed as: $\beta_A(\bar{X}_A - \bar{X}_B) + (\beta_A - \beta_B)\bar{X}_B$, the focus is on members of group A and we consider the hypothetical situation of what happens if they had the average characteristics of members of group B. Renaming group A as the treatment group and group B as the control group, we can see that this decomposition is closely related to the parameter of interest known as the average treatment on the treated (ATT). On the other hand, in the opposite case where the focus is on members of group B and we think about what happens if they had the average characteristics of members of group A, the parameter being estimated is the average treatment on the untreated (ATUT).

Recently, Elder *et al.* (2010) suggest that the pooled BO decomposition without a group-specific indicator should not be used to distinguish between explained and unexplained gaps. They instead suggest the coefficient on a group indicator from an OLS regression for obtaining a single measure of the unexplained gap, and discuss how this coefficient can essentially be viewed as a weighted average of the two different ways of doing a BO decomposition. A parallel discussion of this issue can be found in Angrist and Pischke (2009) when discussing the different causal parameters that matching and OLS estimate. They note that whereas matching uses the distribution of covariates among the treated to weight covariate specific estimates into an estimate of the ATT, regression produces a variance weighted average of these effects. What this translates into is that while the ATT estimate places most weight on covariate cells containing those who are most likely to be treated, regression places most weight on covariate cells where the conditional variance of treatment status is largest, which occurs where there are equal number of treatment and control observations (Angrist and Pischke, 2009, p.76).

Estimating gaps using the OLS approach has been applied to the measurement of union wage premiums (e.g., Lewis, 1986), racial test score gaps (e.g., Fryer and Levitt, 2004), and racial wage gaps (e.g., Neal and Johnson, 1996). More recently, Lundborg *et al.* (2010) adopt this approach in decomposing the wage gap between obese and non-obese individuals.

An important advantage of viewing our problem as a decomposition problem rather than a treatment effects problem is that we can focus on the relative importance of different sets of variables in explaining the observed gap. This can be accomplished by estimating various OLS models using different combinations of characteristics. On the other hand, a treatment effects approach would focus on providing a single 'best' estimate of the impact of obesity. Importantly, the decomposition approach also does not require us to make the conditional independence assumption (CIA) underlying regression or matching estimators that attempt to measure causal effects. This assumption states that conditional on some set of covariates, the potential outcomes for the obese and non-obese are independent of their group status. In practice, unless a rich set of covariates are available that are related to both labor market outcomes and obesity, it can be difficult to fulfil this assumption.

In our paper, we therefore mainly focus on applying the pooled regression decomposition approach in order to determine the relative importance of education, demographic characteristics, psychological factors, cognitive skills and health in explaining the obesity gap among unemployed Germans. Since previous studies have sometimes observed differences in the effect of body size on the wages of men and women (e.g., Averett and Korenman, 1999; Baum and Ford, 2004; Cawley, 2004), we provide estimates separately for men and women. In addition to estimating gaps between the obese (BMI $\geq$ 30) and persons of healthy weight (18.5 $\leq$ BMI < 25), we also conduct similar decomposition exercises for comparing persons who are overweight (25 $\leq$ BMI < 30) with persons of healthy weight.

4.2 Matching

An alternative approach we adopt to estimate the gap in labor market outcomes between obese and non-obese persons is to use an approach from the treatment effects literature – matching. Utilizing the matching estimator as a tool to perform decompositions instead of estimating average treatment effects is similar in spirit to the papers by Nopo (2008) and Frölich (2007). Unlike in the standard application of matching in the evaluation literature, when matching is used to perform a decomposition, it is not necessary that the CIA holds. Any observable that is not measured simply falls into the residual term.

In this paper, we report our matching estimates based on kernel matching. One major advantage of kernel matching is the lower variance which is achieved because more information is used for constructing counterfactual outcomes. This could be important as our groups of obese and non-obese persons are rather small. An additional advantage of kernel matching comes from the results of Heckman, Ichimura, and Todd (1998) who derive the asymptotic distribution of these estimators and show that bootstrapping is valid to draw inference for this matching method. This allows us to circumvent the issues raised by Abadie and Imbens (2008), pointing out that bootstrap methods are invalid for nearest neighbor matching.

Before applying kernel matching, assumptions have to be made regarding the choice of the kernel function and the bandwidth parameter h. The choice of the kernel appears to be relatively less important in practice. What is seen as more important is the choice of the bandwidth parameter h with the following trade-off arising: high values of h yield a smoother estimated density function, producing a better fit and a decreasing variance between the estimated and the true underlying density function. On the other hand, underlying features may be smoothed away by a large h, leading to a biased estimate. The choice of h is therefore a compromise between a small variance and an unbiased estimate of the true density function. We follow the rule of thumb approach as proposed by Silverman (1986), but also test the sensitivity of the results with respect to different bandwidth choices.

We provide matching estimates as a robustness check for several reasons. In addition to estimating a different parameter, a semi-parametric matching approach differs from the parametric BO decomposition approach in two other aspects. First, the regression function is no longer specified as linear. Second, the adjusted mean labor market outcome is simulated only for the common support subpopulation. While this latter issue is largely recognized in the program evaluation literature, it has until recently not received much attention in decomposition analysis. For example, by not considering the common support restriction, the BO decomposition is implicitly based on linear extrapolation and an 'out-of-support assumption'. Put another way, it becomes necessary to assume that the linear estimators of the outcomes are also valid out of the support region of individual characteristics for which they were estimated.

5. RESULTS

We examine the gap between overweight and healthy weight persons, and the gap between obese and healthy weight persons on two sets of outcomes variables. The first set relates to the job search process of the unemployed individuals in wave 1 where we observe: (i) the reservation wage and (ii) the search intensity (measured as the number of search channels used). As already mentioned above we observe these outcomes only for individuals still unemployed and actively searching for work in wave 1, such that the sample size for these outcomes is smaller than for the second set of outcomes which relate to the employment status in wave 2. In addition to the employment status in wave 2, we also observe the realized wage for those who found a job. We employ OLS models for all outcomes except for employment where the outcome is binary. For models with employment as the dependent variable, we employ probit models and report marginal effects at the mean values of the covariates. All estimations are conducted separately by gender.

5.1 Estimates of the gap using OLS

Table 4 presents estimates of the gap in outcomes between overweight and healthy weight men. The column labelled 'raw gap' is the unadjusted mean difference in outcomes between the two groups, where it can be seen that significant differences exist for log reservation wages in wave 1 and employment status in wave 2 – overweight men are likely to have higher reservation wages than healthy weight men, and are also more likely to be employed in wave 2. Columns (1) to (5) each control for different sets of characteristics in order to determine how each of the characteristics affect the obesity gap. Column (6) includes education, socio-demographic and personality variables in a single regression. Column (7) includes all the characteristics in column (6) with the further addition of health variables. Finally, column (8) includes all prior variables as well as additional measures for cognitive skills. The employment history variables in the 'other demographics' category are useful in trying to control for the labor supply of individuals in the two weight categories in each of our pairwise comparisons in our regression models,. This way, any observed gap in employment and wage outcomes is more likely to be due to labor demand as opposed to labor supply. Column (3) in Table 4 shows that for overweight men, these set of variables are instrumental in reducing the significant raw gap in log reservation wages. By and large, any gaps found using OLS regressions between overweight and health weight men are eliminated once we control for education, socio-demographic and other characteristics. For example, in column (8), it can be seen that the raw gap in log reservation wages is 0.147, but that this is reduced to 0.064 and not significant any more once we control for our full set of characteristics.

* Table 4 about here *

Table 5 presents estimates of the gap in outcomes between obese and healthy weight men. As with the overweight vs. healthy weight comparison for men, there are no significant gaps in labor market outcomes once education, socio-demographic and other characteristics are controlled for.

* Table 5 about here *

For women, the raw data in Table 6 suggest that overweight women are likely to have significant lower reservation wages than healthy weight women, the opposite of what was found for men. In addition, overweight women are also less likely than healthy weight women to be employed in wave 2, and also to have lower log hourly wages in wave 2 (see Table 6). However, once the regression models controls for various sets of relevant characteristics (columns (6) to (8)), the conditional gaps are no longer found to be significant.

* Table 6 about here *

On the other hand, we find that there are interesting and significant conditional gaps in search and labor market outcomes for obese women. By wave 2, the model in column (6) of Table 7, which has controls for education, socio-demographic variables and personality, reveals that obese women are about 11 percentage points less likely to be employed relative to healthy weight women and they also earn on average 0.094 less in terms of log hourly wages. The finding that obese women have lower employment levels is noteworthy and surprising as obese women had relatively lower reservation wages (-0.139 log points) and made 4.7 more job applications on average.

If the obesity gap is due to health limitations, we expect the obesity coefficient to become smaller and insignificant once we control for health. When we control for health (column 7), the effects on employment are no longer significant. This possibly suggests that it is health limitations among obese women that are affecting their probability of finding employment and not obesity per se. In column (8), where cognitive skills are also controlled for, the effects on wages also lose their statistical significance, echoing the findings in Lundborg *et al*. (2010) that the negative association of obesity and earnings could be operating mainly due to skill differences between the obese and non-obese.

Interestingly, the conditional gap in search intensity between obese women and healthy weight women remains statistically significant even after we control for health and cognitive skills. Looking at the search and labor market outcomes together as a whole, one possible interpretation of our results is that obese women need to search harder in order to achieve similar employment and wage outcomes as healthy weight women.

* Table 7 about here *

5.2 Estimates of the gap using matching

As a robustness check, we also use a matching estimator to provide estimates of the obesity gap. We focus on the results from a propensity score specification that does not include any potentially endogenous variables such as health. In order to not reduce the sample sizes even more, we also omit the cognitive skill variables and use the specification in column (6) of the OLS regressions.

Based on kernel matching estimates using the Epanechnikov kernel and experimenting with alternative bandwidths, there appears to no significant effects of obesity on labor market outcomes for men, and only significant results for obese women. The matching results for obese women largely reflect the OLS estimates reported in column (6) of Table 7.

* Table 8 about here *

* Table 9 about here *

Overall, the matching estimates which do not control for health status suggest that only obese women suffer some labor market consequences. The finding that the negative consequences of obesity on labor market outcomes are greater for females than for males is consistent with the findings from other studies analysing the impact of obesity on labour market outcomes (e.g., Baum and Ford, 2004; Cawley, 2004; Harper, 2000; Morris, 2007; Sargent and Blanchflower, 1994).

6. CONCLUSIONS

The economics literature has focused on estimating the effects of many different forms of discrimination. Like other forms of discrimination, weight discrimination is highly dependent on public perception. It is therefore a useful exercise to carry out empirical studies on many different subgroups of the population to measure the full extent of any discrimination that might exist in society. In this paper, we examined the issue of whether obese job applicants that newly enter unemployment in Germany have different job search behaviors from non-obese applicants and whether they are regarded differently by employers. The thought experiment was to hold a 'beauty contest' where employers choose whom to hire first from a line up of unemployed persons. Unlike other observational studies which are generally based on obese and non-obese individuals who might already be at different points in the job ladder (e.g., household surveys), in this case, individuals all start from the same point – they are unemployed and possess limited skills. In the sense that we are trying to create a hypothetical experiment whereby individuals newly entering unemployment are assigned to different weight groups, our study design might be viewed as being somewhere in-between an experimental study and a standard observational study.

Our results suggest that no discrimination occurs for overweight males and females. Obese men also do not appear to suffer any forms of discrimination. The only group we find in our data experiencing any possible form of labor market discrimination is obese women. Despite having lower reservation wages and making more job applications, obese women were found to have lower employment rates than healthy weight women when we do not account for differences in health and cognitive skills. It appears, however, that much of the penalty obese women are paying is mediated through health and cognitive skills. This is because when these variables are controlled for, the estimated gaps in employment and wages for obese women are no longer statistically significant.

It remains to be determined on the labor supply side what the true nature of the relationship between obesity and health is. Our data do not allow us to disentangle whether health problems amongst the obese might be the result of past discrimination, or whether obesity causes health problems. All we can say at this point is that health appears to affect the ability of obese unemployed women to transition smoothly to employment. Further research on understanding the interaction between obesity, health and labor market outcomes will be useful.

REFERENCES

Abadie, A. and G. Imbens (2008). On the failure of the bootstrap for matching estimators. *Econometrica* 76: 1537–1557.

Aigner, D. and G. Cain (1977). Statistical theories of discrimination in labor markets. *Industrial and Labor Relations Review* 30: 175–187.

Altonji, J. and R. Blank (1999). Race and gender in the labor market. In Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3C: 3143–3259. Amsterdam: North-Holland.

Andreyeva T, R. Puhl and K. Brownell. (2008). Changes in perceived weight discrimination among Americans: 1995–1996 through 2004–2006. *Obesity* 16: 1129–1134.

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

Averett, S. and S. Korenman (1999). Black-white differences in social and economic consequences of obesity. *International Journal of Obesity* 23: 166–173.

Baum, C. and W. Ford. (2004). The wage effects of obesity: a longitudinal study. *Health Economics* 13: 885–899.

Becker, G. (1957). The *Economics of Discrimination*. Chicago: University of Chicago Press.

Berghöfer, A., T. Pischon, T. Reinhold, C. Apovian, A. Sharma and S. Willich. (2008). Obesity prevalence from a European perspective: a systematic review. *BMC Public Health* 8: 200 (doi:10.1186/1471-2458-8-200).

Blinder, A. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources* 8: 436–455.

Brunello, G. and B. D'Hombres. (2007). Does body weight affect wages? Evidence from Europe, *Economics and Human Biology* 5: 1-19.

Brunello, G., P. Michaud and A. Sanz-de-Galdeano. (2009). The rise of obesity in Europe: an economic perspective, *Economic Policy* 57: 553-596.

Caliendo, M., A. Falk, L. Kaiser, H. Schneider, A. Uhlendorff, G. J. Van den Berg und K. F. Zimmermann (2010): The IZA evaluation dataset: towards evidence-based labour policy-making, Working Paper, IZA Bonn.

Card, D. J. Kluve and A. Weber. (2009). Active labor market policy evaluations: a meta-analysis. IZA Working Paper No. 4002.

Cawley, J. (2000). Body weight and women's labor market outcomes. Technical Report Working Paper No. 7841, NBER, Cambridge, MA.

Cawley, J. (2004). The impact of obesity on wages. *Journal of Human Resources* 39: 452–474.

Cawley, J. (2007). The labor market impacts of obesity, in *Obesity, Business, and Public Policy*, Z. Acs and A. Lyles (eds.). Northampton: Edward Elgar.

Cawley, J. and S. Danzinger (2005). Morbid obesity and the transition from welfare to work. *Journal of Policy Analysis and Management* 24: 727-743.

Cawley J, J. Rizzo and K. Haas. (2007). Occupation-specific absenteeism costs associated with obesity and morbid obesity. *Journal of Occupational and Environmental Medicine* 49:1317-1324.

Conley, D. and R. Glauber. (2006). Gender, body mass, and socioeconomic status: new evidence from the PSID, *Advances in Health Economics and Health Services Research* 17: 253-275.

Finkelstein E, C. Fiebelkorn and G. Wang. (2005). The costs of obesity among full-time employees. *American Journal of Health Promotion* 20: 45-51.

Flegal K., M. Carroll, C. Ogden and C. Johnson (2002). Prevalence and trends in obesity among U.S. adults, 1999–2000. *Journal of the American Medical Association* 288: 1723-1727.

Frölich, M. (2007). Propensity score matching without conditional independence assumption with an application to the gender wage gap in the United Kingdom. *Econometrics Journal* 10, 359–407.

Fryer, R. and S. Levitt (2004). Understanding the black-white test score gap in the first two years of school. *Review of Economics and Statistics* 86: 447–464.

Garcia, J. and C. Quintana-Domeque (2006). Obesity, employment and wages in Europe, *Advances in Health Economics and Health Services Research* 17: 187-217.

Harper, B. (2000). Beauty, stature and the labour market: a British cohort study. *Oxford Bulletin of Economics and Statistics*, 62: 771–801.

Heckman, J., H. Ichimura, and P. Todd (1998). Matching as an econometric evaluation estimator. *Review of Economic Studies* 65: 261–294.

Lewis, G. (1986). *Union Relative Wage Effects: A Survey*. Chicago: The University of Chicago Press.

Loh, E. (1993). “The economic effects of physical appearance.” *Social Science Quarterly* 74: 420–438.

Lundborg, P., P. Nystedt and D. Rooth. (2010). No country for fat men? Obesity, earnings, skills, and health among 450,000 Swedish men. IZA Working Paper No. 4775.

Morris, S. (2007). The impact of obesity on employment. *Labour Economics* 14: 413–433.

Neal, D. and W. Johnson (1996). The role of premarket factors in black-white wage differences. *Journal of Political Economy* 104: 869–895.

Neumark, D. (1988).Employers discriminatory behaviour and the estimation of wage discrimination. *Journal of Human Resources*, 23: 812-860.

Nopo, H. (2008). Matching as a tool to decompose wage gaps. *Review of Economics and Statistics* 90: 290–299.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review* 14: 693–709.

Pagan, J. and A. Davila (1997). Obesity, occupational attainment and earnings. *Social Science Quarterly* 78: 756–770.

Puhl R. and K. Brownell. (2001). Bias, discrimination, and obesity. *Obesity Research* 9: 788–905.

Register, C. and D. Williams. (1980). Wage effects of obesity among young workers. *Social Science Quarterly* 71: 130–141.

Riach, P. and J. Rich. (2002). Field experiments of discrimination in the market place. *Economic Journal* 112, F480-F518.

Roehling, M. (1999). Weight-based discrimination in employment: psychological and legal aspects. *Personnel Psychology* 52: 969-1016.

Roehling M., P. Roehling and S. Pichler. (2007). The relationship between body weight and perceived weight-related employment discrimination: the role of sex and race. *Journal of Vocational Behavior* 71: 300–318.

Roehling M., S. Pilcher, F. Oswald and T. Bruce. (2008). The effects of weight bias on job-related outcomes: a meta-analysis of experimental studies. Academy of Management Annual Meeting, Anahiem, CA.

Rooth, D. (2009). Obesity, attractiveness and differential treatment in hiring: a field experiment. *Journal of Human Resources* 44: 710-735.

Sargent, J. and D. Blanchflower (1994). Obesity and stature in adolescence and earnings in young adulthood: Analysis of a british birth cohort. *Archives of Pediatrics and Adolescent Medicine* 148: 681–687.

Silverman, B. (1986). *Density Estimation for Statistics and Data Analysis*. London: Chapman & Hall.

Table 1: Sample Sizes

	Full Sample		Searching for Job in Wave 1	
	Men	Women	Men	Women
$18.5 \leq$ BMI < 25	391	424	192	272
$25 \leq$ BMI < 30	284	159	153	107
BMI ≥ 30	109	90	56	59
Total	784	673	401	438

Note: People with a BMI smaller than 18.5 are excluded. We also exclude individuals with missing values in key regressors.

Table 2: Socio-Demographic Characteristics by BMI Group

Characteristic	(Men) 18.5 ≤ BMI < 25	(Men) 25 ≤ BMI < 30	(Men) BMI ≥ 30	(Women) 18.5 ≤ BMI < 25	(Women) 25 ≤ BMI < 30	(Women) BMI ≥ 30
West Germany	0.68	0.75	0.76	0.72	0.73	0.63
Female	0.00	0.00	0.00	1.00	1.00	1.00
German citizenship	0.96	0.95	0.94	0.93	0.96	0.96
Migration background 1 (1=yes)	0.17	0.20	0.17	0.21	0.18	0.14
Migration background 2 (1=yes)	0.13	0.14	0.13	0.17	0.14	0.12
Age	31.07	36.32	38.28	35.70	38.14	40.92
Age (17-24 years)	0.40	0.23	0.17	0.17	0.16	0.13
Age (25-34 years)	0.27	0.20	0.25	0.29	0.21	0.16
Age (35-44 years)	0.17	0.30	0.26	0.33	0.33	0.21
Age (45-55 years)	0.16	0.28	0.33	0.21	0.31	0.50
Married (or cohabiting)	0.21	0.36	0.44	0.43	0.57	0.54
One child	0.17	0.13	0.17	0.22	0.19	0.23
Two (or more) children	0.10	0.14	0.14	0.18	0.21	0.10
Unemplomyent benefit recipient (yes)	0.74	0.79	0.80	0.71	0.78	0.70
Level of UB (missing=0)	453.79	617.63	661.60	391.10	435.21	386.06
Level of UB (log(ben+1), missing=0)	4.34	4.73	4.98	3.96	4.62	3.91
School leaving degree						
None, special needs, other	0.03	0.03	0.01	0.01	0.03	0.02
Lower secondary school	0.28	0.28	0.49	0.17	0.21	0.30
Middle secondary school	0.36	0.40	0.28	0.34	0.47	0.50
Specialized upper secondary school	0.33	0.29	0.22	0.48	0.29	0.18
Internal or external professional training, others	0.63	0.64	0.66	0.61	0.73	0.72
Technical college or university degree	0.24	0.27	0.21	0.32	0.18	0.18
Months in unemployment (divided by age-18)	0.86	0.61	0.74	0.60	0.79	0.79
Months in employment (divided by age-18)	7.69	8.64	9.56	6.91	8.18	7.98
Month of entry						
June	0.26	0.28	0.27	0.30	0.31	0.34
October	0.34	0.36	0.33	0.34	0.43	0.30
February	0.40	0.36	0.40	0.36	0.26	0.36

(continued)

Characteristic	(Men) 18.5 ≤ BMI < 25	(Men) 25 ≤ BMI < 30	(Men) BMI ≥ 30	(Women) 18.5 ≤ BMI < 25	(Women) 25 ≤ BMI < 30	(Women) BMI ≥ 30
Employment status before unemployment						
Employed	0.59	0.64	0.65	0.63	0.58	0.66
Subsidized employment	0.04	0.05	0.11	0.03	0.04	0.04
School, apprentice, military, etc.	0.29	0.21	0.14	0.16	0.13	0.12
Maternity leave	0.00	0.00	0.00	0.10	0.13	0.08
Other	0.08	0.10	0.10	0.08	0.11	0.10
Time between UE and interview:						
7 weeks	0.02	0.02	0.02	0.03	0.02	0.02
8	0.18	0.18	0.20	0.13	0.13	0.14
9	0.17	0.12	0.14	0.14	0.10	0.14
10	0.21	0.17	0.19	0.21	0.26	0.17
11	0.19	0.21	0.24	0.21	0.24	0.23
12	0.07	0.09	0.08	0.10	0.09	0.11
13	0.06	0.06	0.03	0.03	0.04	0.01
14 or more	0.11	0.15	0.10	0.15	0.11	0.17
Alcohol Consumption						
almost every day	0.08	0.08	0.05	0.03	0.01	0.01
3-4 times a week	0.14	0.14	0.13	0.07	0.05	0.04
1-2 times a week	0.35	0.37	0.26	0.27	0.23	0.14
more seldom than once a week	0.28	0.25	0.29	0.43	0.43	0.40
never	0.16	0.15	0.28	0.20	0.29	0.40
Local UE Rate at time of the interview						
below 5% (ref.)	0.18	0.19	0.19	0.21	0.13	0.13
5-10%	0.44	0.44	0.47	0.45	0.54	0.43
10-15%	0.24	0.26	0.26	0.22	0.24	0.28
15+%	0.14	0.11	0.08	0.11	0.09	0.16
N	391	284	109	424	159	90

Table 3: Other Characteristics by BMI Group

Characteristic	(Men) 18.5 ≤ BMI < 25	(Men) 25 ≤ BMI < 30	(Men) BMI ≥ 30	(Women) 18.5 ≤ BMI < 25	(Women) 25 ≤ BMI < 30	(Women) BMI ≥ 30
Personality Variables						
Internal Locus of Control (7 = high, 1 = low)	5.13	5.17	4.97	5.12	4.89	4.93
Openness (7= high, 1 = low)	5.09	5.13	4.98	5.04	4.88	5.02
Conscientiousness (7= high, 1 = low)	5.99	6.11	6.01	6.21	6.19	6.14
Extraversion (7= high, 1 = low)	4.99	4.99	5.04	5.20	5.23	5.25
Neuroticism (7= high, 1 = low)	3.40	3.41	3.88	3.84	3.93	3.99
Cognitive Skills Test 1 (share of correct answers)	0.68	0.72	0.68	0.63	0.60	0.58
Cognitive Skills Test 2 (number of correct items)	5.04	5.03	4.90	5.76	5.44	5.53
General Health Condition (1 = very good, 5 = bad)	1.75	2.04	2.27	1.81	2.25	2.48
Emotional Impairment in last 2 months (1 = always, 5 = never)	4.28	4.20	4.04	4.06	4.05	3.89
Physical Impairment in last 2 months (1 = always, 5 = never)	4.47	4.33	4.11	4.21	3.96	3.92
Smoking (1 = yes, 2 = no)	1.47	1.54	1.57	1.61	1.70	1.60
N	391	284	109	424	159	90

Note:
The first cognitive skills test comprises three calculation exercises where we report the share of correct answers. The second test counts the number of correctly remembered words from a list of 10 which were read out to the respondents. The number of observations is lower for these questions. For men we observe 340, 244 and 98 in the three weight groups (lowest to highest); for women we have 343, 134, and 71 observations respectively.

Table 4: OLS Regressions of Estimated Gaps: Overweight Men versus Healthy Weight Men

Outcome	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Reservation Wage	0.147***	0.115***	0.048	0.135***	0.154***	0.144***	0.052	0.06	0.064
Number of Job Applications	1.218	0.708	1.994	0.753	-0.073	1.210	0.936	0.805	0.24
Employed in Wave 2	0.066*	0.052	0.028	0.053	0.069*	0.081**	0.02	0.029	0.027
Log Hourly Wages at Wave 2	0.069	0.069	-0.025	0.055	0.079	0.063	-0.020	-0.025	-0.008
Controls for education		✓					✓	✓	✓
Controls for other demographics			✓				✓	✓	✓
Controls for personality				✓			✓	✓	✓
Controls for cognitive skills					✓				✓
Controls for health						✓		✓	✓
N for outcome 1	327	327	327	327	277	327	327	327	277
N for outcome 2	324	324	324	324	275	324	324	324	275
N for outcome 3	675	675	675	675	564	675	675	675	564
N for outcome 4	400	400	400	400	336	400	400	400	336

Note:
Education variables are: school leaving degree (none, lower secondary, middle secondary, specialized secondary, professional training, technical college or university degree).
Other demographic variables are: West Germany, citizenship, married, number of children (0, 1, 2+), unemployment benefit recipient, level of benefits, age (17-24, 25-34, 35-44, 45-55), months in unemployment, months in employment, month of entry into unemployment, employment status before unemployment (employed, subsidized employment, school/apprentice/military, maternity leave, other), local unemployment rate (<5%, 5-10%, 10-15%,15+%), alcohol consumption (almost every day, 3-4 times a week, 1-2 times a week, more seldom than once a week, never).
Personality variables are: openness, conscientiousness, extraversion, neuroticism, internal locus of control index.
Cognitive skill variables are: three tests on arithmetic (1 if correct, 0 if incorrect) and one test on word recall from a list of ten words (using number of words recalled).
Health variables are: general health condition (1=very good, 5=bad), emotional impairment in last 2 months (1=always, 5=never), physical impairment in last 2 months (1=always, 5=never), smoking.
Significant at the: *10 percent level; **5 percent level; ***1 percent level.

Table 5: OLS Regressions of Estimated Gaps: Obese Men versus Healthy Weight Men

Outcome	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Reservation Wage	0.057	0.064	-0.003	0.104	0.085	0.053	0.049	0.063	0.084
Number of Job Applications	0.868	0.494	0.987	0.842	-0.177	1.306	-0.013	0.479	-1.552
Employed in Wave 2	-0.019	-0.029	-0.097*	-0.008	-0.004	0.029	-0.076	-0.049	-0.058
Log Hourly Wages at Wave 2	-0.007	0.011	-0.078	0.011	-0.006	-0.008	-0.043	-0.061	-0.057
Controls for education		✓					✓	✓	✓
Controls for other demographics			✓				✓	✓	✓
Controls for personality				✓			✓	✓	✓
Controls for cognitive skills					✓				✓
Controls for health						✓		✓	✓
N for outcome 1	232	232	232	232	200	232	232	232	200
N for outcome 2	231	231	231	231	200	231	231	231	200
N for outcome 3	500	500	500	500	421	500	500	500	421
N for outcome 4	292	292	292	292	244	292	292	292	244

Note:
Education variables are: school leaving degree (none, lower secondary, middle secondary, specialized secondary, professional training, technical college or university degree).
Other demographic variables are: West Germany, citizenship, married, number of children (0, 1, 2+), unemployment benefit recipient, level of benefits, age (17-24, 25-34, 35-44, 45-55), months in unemployment, months in employment, month of entry into unemployment, employment status before unemployment (employed, subsidized employment, school/apprentice/military, maternity leave, other), local unemployment rate (<5%, 5-10%, 10-15%,15+%), alcohol consumption (almost every day, 3-4 times a week, 1-2 times a week, more seldom than once a week, never).
Personality variables are: openness, conscientiousness, extraversion, neuroticism, internal locus of control index.
Cognitive skill variables are: three tests on arithmetic (1 if correct, 0 if incorrect) and one test on word recall from a list of ten words (using number of words recalled).
Health variables are: general health condition (1=very good, 5=bad), emotional impairment in last 2 months (1=always, 5=never), physical impairment in last 2 months (1=always, 5=never), smoking.
Significant at the: *10 percent level; **5 percent level; ***1 percent level.

Table 6: OLS Regressions of Estimated Gaps: Overweight Women versus Healthy Weight Women

Outcome	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Reservation Wage	-0.082**	-0.019	-0.012	-0.078*	-0.092*	-0.062	-0.002	0.01	-0.004
Number of Job Applications	0.424	1.011	1.538	-0.047	0.768	0.500	1.848	1.871	2.277
Employed in Wave 2	-0.107**	-0.083*	-0.063	-0.095**	-0.111**	-0.061	-0.048	-0.011	-0.037
Log Hourly Wages at Wave 2	-0.093*	-0.016	-0.088*	-0.083*	-0.089*	-0.091*	-0.020	-0.021	-0.005
Controls for education		✓					✓	✓	✓
Controls for other demographics			✓				✓	✓	✓
Controls for personality				✓			✓	✓	✓
Controls for cognitive skills					✓				✓
Controls for health						✓		✓	✓
N for outcome 1	367	367	367	367	290	367	367	367	290
N for outcome 2	363	363	363	363	287	363	363	363	287
N for outcome 3	583	583	583	583	457	583	583	583	457
N for outcome 4	358	358	358	358	293	358	358	358	293

Note:
Education variables are: school leaving degree (none, lower secondary, middle secondary, specialized secondary, professional training, technical college or university degree).
Other demographic variables are: West Germany, citizenship, married, number of children (0, 1, 2+), unemployment benefit recipient, level of benefits, age (17-24, 25-34, 35-44, 45-55), months in unemployment, months in employment, month of entry into unemployment, employment status before unemployment (employed, subsidized employment, school/apprentice/military, maternity leave, other), local unemployment rate (<5%, 5-10%, 10-15%,15+%), alcohol consumption (almost every day, 3-4 times a week, 1-2 times a week, more seldom than once a week, never).
Personality variables are: openness, conscientiousness, extraversion, neuroticism, internal locus of control index.
Cognitive skill variables are: three tests on arithmetic (1 if correct, 0 if incorrect) and one test on word recall from a list of ten words (using number of words recalled).
Health variables are: general health condition (1=very good, 5=bad), emotional impairment in last 2 months (1=always, 5=never), physical impairment in last 2 months (1=always, 5=never), smoking.
Significant at the: *10 percent level; **5 percent level; ***1 percent level.

Table 7: OLS Regressions of Estimated Gaps: Obese Women versus Healthy Weight Women

Outcome	Raw gap	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Reservation Wage	-0.214***	-0.148***	-0.163***	-0.212***	-0.212***	-0.187***	-0.139**	-0.123**	-0.101
Number of Job Applications	3.952*	4.179*	4.472**	3.762*	3.860*	4.350*	4.660**	5.200**	5.257**
Employed in Wave 2	-0.165***	-0.138**	-0.129**	-0.155***	-0.158***	-0.114**	-0.118**	-0.082	-0.055
Log Hourly Wages at Wave 2	-0.198***	-0.104*	-0.167***	-0.204***	-0.197***	-0.164***	-0.094*	-0.092*	-0.082
Controls for education		✓					✓	✓	✓
Controls for other demographics			✓				✓	✓	✓
Controls for personality				✓			✓	✓	✓
Controls for cognitive skills					✓				✓
Controls for health						✓		✓	✓
N for outcome 1	321	321	321	321	254	321	321	321	254
N for outcome 2	318	318	318	318	252	318	318	318	252
N for outcome 3	514	514	514	514	399	514	514	514	399
N for outcome 4	320	320	320	320	260	320	320	320	260

Note:
Education variables are: school leaving degree (none, lower secondary, middle secondary, specialized secondary, professional training, technical college or university degree).
Other demographic variables are: West Germany, citizenship, married, number of children (0, 1, 2+), unemployment benefit recipient, level of benefits, age (17-24, 25-34, 35-44, 45-55), months in unemployment, months in employment, month of entry into unemployment, employment status before unemployment (employed, subsidized employment, school/apprentice/military, maternity leave, other), local unemployment rate (<5%, 5-10%, 10-15%,15+%), alcohol consumption (almost every day, 3-4 times a week, 1-2 times a week, more seldom than once a week, never).
Personality variables are: openness, conscientiousness, extraversion, neuroticism, internal locus of control index.
Cognitive skill variables are: three tests on arithmetic (1 if correct, 0 if incorrect) and one test on word recall from a list of ten words (using number of words recalled).
Health variables are: general health condition (1=very good, 5=bad), emotional impairment in last 2 months (1=always, 5=never), physical impairment in last 2 months (1=always, 5=never), smoking.
Significant at the: *10 percent level; **5 percent level; ***1 percent level.

Table 8: Matching Estimates of the Gap

Overweight Men versus Healthy Weight Men

Outcome	Mean of Outcome for Healthy Weight Men	Kernel Matching (bw = 0.02)	Kernel Matching (bw = 0.06)	Kernel Matching (bw = 0.2)	Treated N	Control N
Log Reservation Wage	1.97	0.065	0.072	0.085	146	181
Number of Job Applications	15.29	0.778	0.808	0.999	144	180
Employed in Wave 2	0.62	-0.001	0.011	0.019	284	391
Log Hourly Wages at Wave 2	2.15	-0.026	-0.015	0.008	176	224

Obese Men versus Healthy Weight Men

Outcome	Mean of Outcome for Healthy Weight Men	Kernel Matching (bw = 0.02)	Kernel Matching (bw = 0.06)	Kernel Matching (bw = 0.2)	Treated N	Control N
Log Reservation Wage	1.97	0.016	0.021	-0.001	51	181
Number of Job Applications	15.29	1.579	-0.924	1.159	51	180
Employed in Wave 2	0.62	-0.075	-0.078	-0.059	109	391
Log Hourly Wages at Wave 2	2.15	-0.111	-0.068	-0.038	68	224

Note: Propensity score models are estimated using the full set of covariates used in Model 6 of the OLS results. Matching is performed using the Epanechnikov kernel. Common support is imposed using the min-max criterion. Imposing common support using 5% trimming resulted in similar results and is not shown. Standard errors are based on bootstrapping with 100 replications.
Significant at the: *10 percent level; **5 percent level; ***1 percent level.

Table 9: Matching Estimates of the Gap

Overweight Women versus Healthy Weight Women

Outcome	Mean of Outcome for Healthy Weight Women	Kernel Matching (bw = 0.02)	Kernel Matching (bw = 0.06)	Kernel Matching (bw = 0.2)	Treated N	Control N
Log Reservation Wage	1.96	-0.012	-0.009	-0.023	104	263
Number of Job Applications	12.63	0.809	0.886	1.036	103	260
Employed in Wave 2	0.70	-0.069	-0.063	-0.067	159	424
Log Hourly Wages at Wave 2	2.11	-0.047	-0.052	-0.067	87	271

Obese Women versus Healthy Weight Women

Outcome	Mean of Outcome for Healthy Weight Women	Kernel Matching (bw = 0.02)	Kernel Matching (bw = 0.06)	Kernel Matching (bw = 0.2)	Treated N	Control N
Log Reservation Wage	1.96	-0.141*	-0.124	-0.134**	58	256
Number of Job Applications	12.63	5.131*	5.001*	4.722*	58	253
Employed in Wave 2	0.70	-0.106	-0.104	-0.118*	90	424
Log Hourly Wages at Wave 2	2.11	-0.128**	-0.119*	-0.126**	49	271

Note: Propensity score models are estimated using the full set of covariates used in Model 6 of the OLS results. Matching is performed using the Epanechnikov kernel. Common support is imposed using the min-max criterion. Imposing common support using 5% trimming resulted in similar results and is not shown. Standard errors are based on bootstrapping with 100 replications.
Significant at the: *10 percent level; **5 percent level; ***1 percent level.