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The Weight Wage Penalty: A Mechanism Approach to Discrimination

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Abstract

The wage weight penalty is a well-established finding in the literature, but not much is known about the mechanisms that bring this phenomenon about. This article aims to provide answers to the question of why overweight and obese people earn less. Using the data of the German Socio-Economic Panel, we conduct three theory-driven litmus tests for mechanisms that explain the weight wage gap: human capital differences, discrimination due to asymmetric information, or taste-based discrimination. Due to conflicting predictions from the three theories, interaction effects between weight and structural conditions serve as the key identification strategy. Results show that for men, productivity-related variables (e.g. education, work experience, occupation, and physical health) almost completely explain the weight-specific variance in wages. In contrast, for women, neither performance nor a lack of information can solve the puzzle of weight-based differences in wages. We therefore conclude that—at least in Germany—overweight and obese women suffer from taste-based discrimination, whereas overweight and obese men earn less due to human capital differences.

Introduction

The negative health consequences of being overweight and obese have been extensively discussed in both scientific publications and the media. It is, for example, now common knowledge that obesity (but not necessarily overweight) is systematically correlated with various measures of health and is a risk factor for several diseases (Walls *et al.*, 2012). The discussion of weight-related health risks has become especially heated because the prevalence of being overweight and obese has substantially increased in Europe (von Ruesten *et al.*, 2011), Asia (Ramachandran and Snehalatha, 2010), and America (Sturm and Hattori, 2013) in the past three decades. Although this trend has been slowing down since 2006 (Ng *et al.*, 2014), overweight and obesity are widespread phenomena: According to the World Health Organization (2015), more than half of the population is classified as either overweight ($25 \leq$ body mass index [BMI] < 30) or obese (BMI ≥ 30) in many countries.[1]

In Europe (Figure 1), the portion of adults suffering from obesity varied between 15 per cent (Moldavia) and nearly 30 per cent (United Kingdom, Andorra, and Turkey) in 2014. In Germany, the obesity rate has risen from 16.5 per cent in 2002 to 18.4 per cent in 2007, and further to 20.2 per cent in 2012 (number derived from the WHO webpage).[2] About 60 per cent of German adults are categorized as at least overweight (BMI ≥ 25) (World Health Organization, 2013) in 2008–2011.

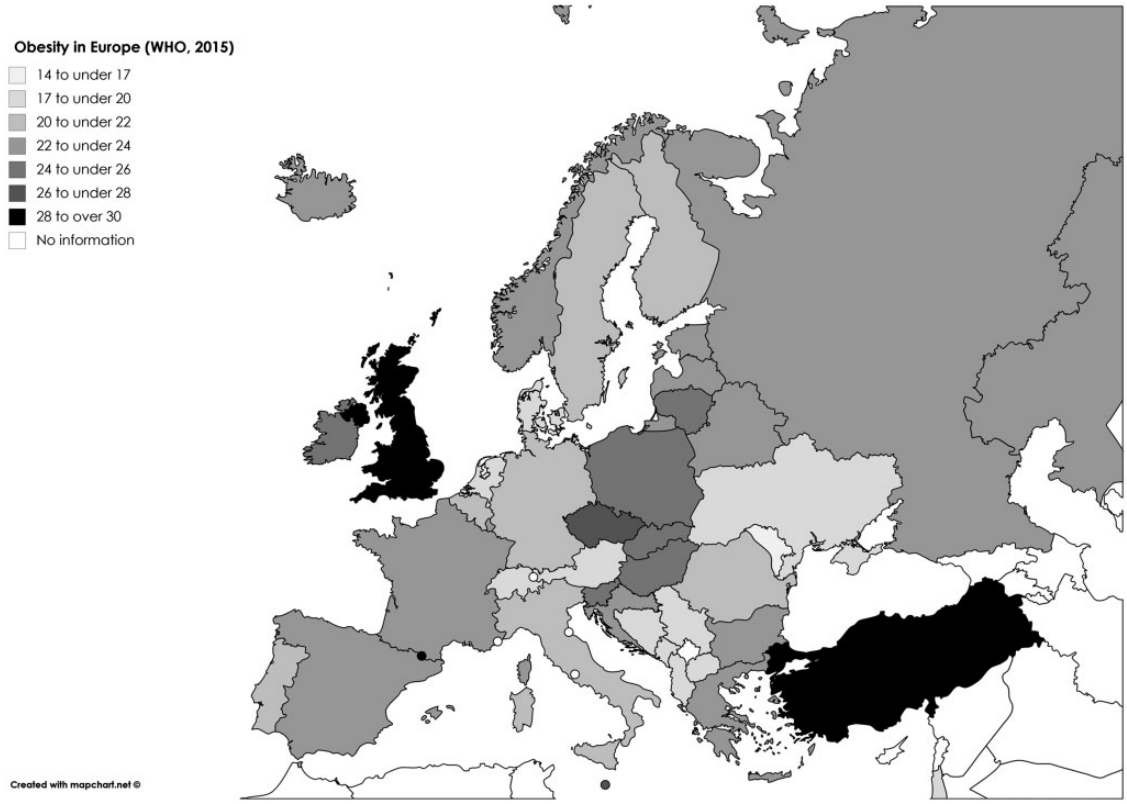

Figure 1. Obesity in Europe

Notes: The percentages are calculated based on the WHO Report (2015). Portions of men and women have been added and divided by two. The concrete percentages in alphabetical order are as follows: Albania (17.6 per cent), Andorra (29.5 per cent), Austria (18.4 per cent), Belarus (23.3 per cent), Belgium (20.4 per cent), Bosnia and Herzegovina (17.9 per cent), Bulgaria (23.2 per cent), Kosovo (no information), Croatia (23.3 per cent), Czech Republic (26.8 per cent), Denmark (19.4 per cent), Estonia (22.6 per cent), Finland (20.6 per cent), France (23.9 per cent), Germany (20.2 per cent), Greece (22.9 per cent), Hungary (24.0 per cent), Iceland (22.8 per cent), Ireland (25.6 per cent), Italy (21.0 per cent), Kazakhstan (23.3 per cent), Latvia (23.6 per cent), Liechtenstein (no information), Lithuania (25.7 per cent), Luxembourg (23.2 per cent), Macedonia (19.6 per cent), Malta (26.6 per cent), Moldavia (14.7 per cent), Monaco (no information), Montenegro (20.0 per cent), The Netherlands (19.9 per cent), Norway (23.2 per cent), Poland (25.1 per cent), Portugal (20.1 per cent), Romania (21.6 per cent), Russia (23.9 per cent), San Marino (no information), Serbia (19.6 per cent), Slovenia (25.1 per cent), Slovakia (25.7 per cent), Spain (23.8 per cent), Sweden (20.6 per cent), Switzerland (19.4 per cent), Turkey (29.4 per cent), Ukraine (19.9 per cent), United Kingdom (28.1 per cent), and Vatican City (no information). The map was created with mapchart.net.

What is at stake then are not only negative individual health consequences but also high costs to national healthcare systems, especially in aging societies.

For these and other reasons (e.g. cultural norms such as weight as an expression of beauty; Hakim, 2010; Wolbring and Riordan, 2016), being overweight and obese has been stigmatized in public discourse and labelled as negative and avoidable individual characteristics that are the result of poor self-control and a lack of knowledge about adequate food habits. An unintended side effect of these public and scientific discussions are negative stereotypes and discrimination. Given the high portion of overweight and obese individuals among the general population, documenting discrimination of this social group would not only add another characteristic to the long list of determinants of social inequality but would also document the discrimination of a majority group. This article therefore analyses the effects of being overweight and obese on wages in the German labour market, with a specific focus on the causal mechanisms that bring about wage differentials.

Empirical studies have documented considerable differences in a variety of social outcomes between normal weight, overweight, and obese individuals. In the United States, overweight and obese individuals, particularly women, have lower incomes, are promoted less often, and have more difficulties finding a job (Register and Williams, 1990; Gortmaker *et al.*, 1993; Hamermesh

and Biddle, 1994; Averett and Korenman, 1996; Bordieri *et al.*, 1997). Similar results have been reported for many European countries (Harper, 2000; Brunello and D'Hombres, 2007; Garcia and Quintana-Domeque, 2007; Greve, 2008; Johansson *et al.*, 2009). Newer studies based on more rigorous methods and better measures of body composition than the BMI (Cawley, 2004; Burkhauser and Cawley, 2008; Wada and Tekin, 2010; Bozoyan and Wolbring, 2011; Kropfhäußer and Sunder, 2015) report weaker effects but find that systematic wage gaps between healthy and overweight respectively obese individuals still persist. Lab and field experiments complement and corroborate these findings from observational studies (Pingitore *et al.*, 1994; Finkelstein *et al.*, 2007; Rooth, 2009; Agerström and Rooth, 2011; Reichert, 2015).

However, neither observational nor experimental studies have been able to contribute a lot to our understanding of the social mechanisms that bring about differences between social groups (for some notable exceptions, see Keuschnigg and Wolbring, 2016). Eminent social scientists have long criticized this unsatisfactory state of research on social inequality. For example, Tilly (1998) argued that the same generative mechanisms of inequality are at work in different social domains, but research on age, ethnicity, gender, and other ascriptive characteristics has so far neglected this structural similarity and mainly proceeds in isolation. Reskin (2003: p. 1) has similarly bemoaned this 'essentialism' and 'balkanization' in her presidential address to the American Sociological Association more than a decade ago, demanding inclusion of 'mechanisms in our models of ascriptive inequality'. Both Diewald and Faist (2011) and Charles and Guryan (2011) have reemphasized this claim and suggested to study the causal pathways of how heterogeneities transform into inequalities.

In this article, we hence propose a theory-driven *modus operandi* that helps us to gain insights into the generative mechanisms at work behind the weight wage penalty. Although we illustrate the method for the case of discrimination of the overweight and obese, the approach is similarly applicable to other characteristics (for the cases of gender and race, see Altonji and Blank, 1999). The proposed mechanism approach studies wage discrimination on the basis of observational data. Although it does share common weaknesses with the conventional residual approach of controlling for all potentially confounding covariates and asking for remaining wage differentials, it allows for a more direct test for discrimination. The foundation for this is the analytical distinction between three different mechanisms that cause wage differences.

Theoretical Background

In this section, we distinguish between human capital theories, on the one hand, and discrimination theories (taste-based and statistical), on the other hand. Human capital theory as proposed by Mincer (1974), Schultz (1961), and Becker (1964) assumes that employees differ in their skills and productivity. Employers have an interest employing productive workers and thus offer them higher payment than less skilled workers. More specifically, human capital theory directly links wages to marginal productivity of labour due to market competition. According to human capital theory, inherited and acquired productivity indicators such as intelligence, education, and work experience should predict wages to a substantial degree. In turn, the theory provides a rationale for the weight wage penalty in the case that productivity is correlated with body weight. In contrast, human capital theory is hardly able to explain the remaining weight-related wage differences for employees with equal productivity.

Theories of statistical discrimination (Arrow, 1973, 1998; Phelps, 1972) share with human capital theory the assumption that marginal productivity of labour affects wages. According to these models, employers prefer to adhere to meritocratic principles and pay employees for their individual achievements. However, information is incomplete and asymmetric, as employers do not know exactly how productive a worker is. The extent of asymmetric information is particularly large for job applicants: Educational credentials, previous employment history, and letters of recommendation simply do not allow a precise evaluation of expected productivity. Hence, according to theories of statistical discrimination, rational employers rely on additional signals, such as the membership to a social group, to improve their productivity estimates in the face of asymmetric information. As with age, gender, and ethnicity, overweight and obesity are such group markers that are readily available and salient in job interviews, which can activate negative stereotypes about one's interaction partner.

In the original versions of the theoretical model, these subjective estimates of ability are formed via Bayesian learning, meaning that rational individuals build their expectations on the information available to them and adapt their expectations in an optimal way if new information becomes available (for an introduction into Bayesian learning, see Lee, 2012). Hence, in the original version of the model, expectations are conditional on the information at hand at a certain point in time and are, on average, correct, but modifications of

the model allow for deviations from Bayesian learning and the formation of false beliefs (Farmer and Terrell, 1996). This adds realism to the model, as individuals are known to be sometimes reluctant to contradictory evidence. For example, Pager and Karafin (2009) empirically showed that prejudiced stereotypes can persist even if conflicting evidence is present. This is also likely for the case of body weight, where strong negative stereotypes are prevalent. For example, as several studies show, many people perceive the overweight and obese as less dutiful, loyal, intelligent, or emotionally stable and more weak-headed, lazy, and insecure (Polinko and Popovich, 2001; Puhl and Brownell, 2001; Roehling *et al.*, 2008; Sikorski *et al.*, 2012).

Clearly, if rational employers act on these stereotypes, they will offer lower wages to overweight and obese applicants. Thus, according to statistical discrimination theories, some individuals suffer (negative discrimination), whereas others profit (positive discrimination), from the ascribed group membership if a non-zero variance in productivity between applicants exists.[3]

However, whereas it pays off for employers to rely on signals that are, on average, correct in situations characterized by asymmetric information, there is no incentive for rational employers to act on false beliefs. Thus, statistical discrimination only occurs if no better, more efficient solution is available. This is in sharp contrast with the next form of discrimination.

Theories of taste-based discrimination ascribe unequal treatment of individuals to affective preferences for and against particular social groups. Becker (1957) modelled this type of discrimination as the price one is willing to incur to avoid interaction with the disliked social group. In other words, the utility of persons with a preference against a certain social group is reduced by contact with the latter. As a consequence, individuals will be willing to interact with such persons only if the expected utility gains from the interaction outweigh these taste-based losses. The theory thereby takes into account the possibility of discrimination by potential employers, co-workers, and customers. Employers, for example, might offer higher wages to members of preferred social groups to avoid engagement of disliked—but no less productive—individuals. Likewise, workers might be willing to forgo income to prevent contact with co-workers belonging to disdained social groups. Customers might buy the same product in a more expensive shop simply because they are served by members of a preferred social group.

As becomes obvious from these examples, preference-based discrimination is costly in monetary terms to the offender. Understanding the cost of unequal treatment as a tax levied on discriminators (Arrow, 1973), the extent of discrimination should decline with rising market competition. In a perfect world, employers can only afford to forgo productive gains by discrimination as long as they are not at risk to be driven out of the market by competitors who do not pay this implicit tax to fulfil their preferences (Goldberg, 1982). More importantly for the following and in contrast to theories of statistical discrimination, the extent of taste-based discrimination will not change if additional information becomes available, as preferences are assumed to be constant. We will exploit this theoretical implication to distinguish empirically the different theoretical explanations.

Testing for Mechanisms of Discrimination

One of the key problems in research on social stratification is to empirically distinguish between the three above-mentioned explanations for wage differences. This holds true both for observational and experimental studies. One promising line of research, we argue, is to investigate the effects under structural conditions that shape individual opportunities (Petersen and Saporta, 2004; Petersen, 2009) and for which theoretical predictions from the explanatory approaches differ (Altonji and Blank, 1999; Mason, 2012). In this article, we rely on several litmus tests to study the nature of discrimination and to empirically distinguish potential mechanisms.

First, we examine whether overweight and obese individuals are as productive as individuals with a healthy weight. By definition, weight-specific wage differences in the face of equal productivity would clearly indicate discrimination. Among the most important productivity characteristics are education, the sum of work experience, intelligence, and health. Furthermore, physical appearance can be a key asset in positions with representative tasks (Hakim, 2010; Hamermesh, 2011). Our first step is therefore to ascertain whether the above-mentioned variables are systematically correlated with body weight. Note that we are not interested in causal effects but in associations. If we find weight-related productivity differences, we will include them in our wage regression models to test whether there are additional mechanisms at work, such as statistical or taste-based discrimination.

Second, job changes are an interesting case to test for statistical discrimination, as asymmetric information is particularly high for first encounters of potential employer and employee. Theories of statistical

discrimination predict that the effect of group membership is highest in this situation and then declines or even disappears: 'once on the job, where they [the employees; C.B. & T.W.] can demonstrate that they have the right characteristics, their wages will rise to the level of others with the right characteristics regardless of the groups to which they belong' (Thurow, 1975: p. 173). In contrast, we do not expect the effects of human capital differences or the extent of taste-based discrimination to be particularly pronounced under these circumstances, as information on individual productivity is scarce and preferences for or against certain social groups are assumed to be stable over time. We test this by including an interaction term between the indicators of body fat (BF) and job changes.

Similarly, taste-based discrimination should not decline with job tenure. As tastes are assumed to be constant in this model, social interactions and measures of actual performance should not change employers' behaviour. However, as Altonji and Blank (1999) explain, asymmetric information declines the longer an individual is employed and the more information on performance and skills becomes available. Altonji and Pierret (2001) provide supportive evidence for this widely neglected implication: As firms learn about the productivity of young workers, group characteristics lose explanatory power, whereas hard-to-observe, productivity-enhancing traits such as intelligence rise in relevance. Thus, our test focuses on the interplay of job tenure with group markers and intelligence. We expect the interaction term between job tenure and body weight to be negative and the interaction between job tenure and intelligence to be positive.

Finally, studying the interaction of obesity with age can reveal further information about the processes at hand. For young and inexperienced employees, lack of information is highest. Potential employers have to make their employment decisions solely on the basis of murky indicators for actual productivity such as degrees, grades, and experiences collected during the interview process. With rising applicant age, more reliable data become available. This additional information includes work experience, further education, areas of specialization, names of previous employers, and duration of job and unemployment episodes. Employers can additionally contact references listed in CVs to ask for first-hand experiences. Thus, as emphasized by Altonji and Pierret (2001), statistical discrimination should be particularly high for young, inexperienced workers and then decline with rising age. Again, we will test this hypothesis by adding an interaction term between weight and age (Table 1).

Data and Methods

Our empirical application of this direct test for discrimination relies on six waves (2002, 2004, 2006, 2008, 2010, and 2012) of the German Socio-Economic Panel (GSOEP; Wagner *et al.*, 2007). The GSOEP is a longitudinal study of private households focusing on all aspects

Table 1. Testing strategy overview

Weight-specific differences in . . .	**with this direction**	**. . . lead to disadvantages for overweight and obese people**
Intelligence	negative	**. . . due to human capital**
Days absent	positive	
Subjective health	negative	
Education	negative	
Work experience full-time	negative	
Work experience part-time	negative	
Experience of being unemployed	positive	
Occupation	positive	
Interaction terms between . . .	**with this direction**	**. . . lead to disadvantages for overweight and obese people**
Body fat percentage X job changes	positive	**. . . due to statistical discrimination**
Body fat percentage X job tenure	negative	
Job tenure X intelligence	positive	
BF percentage X age	negative	
No significant interactions . . .	**. . . lead to**	**disadvantages for overweight and obese people due to taste-based discrimination**

of life. Since 2002, detailed information about body composition in the form of a subjective measurement of body size and height is provided every other year. A focus on Germany has both substantive and methodological reasons. Substantively, Germany offers an interesting case for investigating the weight wage penalty, because—as compared with the United States and other European countries (Figure 1)—the prevalence of obesity is relatively low, making it a highly salient characteristic. At the same time, due to the important role of unions and rigid federal laws protecting employees, the German labour market is quite regulated, leaving less room for discrimination than in other countries. On the methodological side, as we are implementing an observational instead of an experimental approach, it is essential to control for all confounding variables. The GSOEP is ideally suited for this, as it contains high-quality measures for all of the aforementioned control variables.

We restrict the sample to men and women of age between 18 and 66 years, working full- and part-time[4] with a minimum hourly wage of €1. Self-employed persons, trainees, farmers, and pregnant women are excluded. We also drop subjects (21 person-years) whose height fell outside the range of 114–213 centimetres and whose body weight is lower than 31 or higher than 180 kilograms.

As the main explanatory variable, we could use the BMI (kg/m^2). However, the BMI at most only moderately correlates with more reliable measures of body composition (Gallagher *et al.*, 1996; Heyward and Wagner, 2004) and has therefore been heavily criticized as a noisy measure of overweight and obesity (Samaras, 2006; Burkhauser and Cawley, 2008). This is especially true for men, as the BMI does not distinguish between two types of body mass: fat free mass (FFM; mainly muscles and bones) and BF (for a robustness check, see Table A2 in Supplementary Appendix A).

Following Burkhauser and Cawley (2008) and Wada and Tekin (2010), we thus rely on an indirect approach to estimate both constructs (for details, see Bozoyan and Wolbring, 2011; Bozoyan, 2014): First, we estimate FFM and BF in an external data set, the BIA database project, on the basis of bioelectrical impedance analysis using an equation following Kyle *et al.* (2004). Next, we re-estimate the generated values for FFM and BF using only the information available in the GSOEP: sex, age (age^2), weight (weight^2), and height (height^2). The optimal procedure here would be to use self-reported weight and height for the BIA data sample, as the GSOEP only collects subjective information. As this is not possible with the BIA data sample, we control for the presence of an interviewer in the GSOEP following the example of Cawley *et al.* (2005). Sex and age should be unbiased in both data sets. With an R^2 for BF between 0.84 (men) and 0.91 (women), the model fit is quite high, indicating that the two body mass components can be sufficiently approximated with this approach.

To allow for comparability of the GSOEP and the external data set, we randomly drew a BIA data subsample adjusted to match the BMI and sex distributions in the GSOEP 2002 (for a detailed description of this procedure, see Bozoyan and Wolbring, 2011). Finally, we transferred the estimation equation into the GSOEP and calculated both BF and FFM. To account for the generated regressors, we bootstrapped the standard errors in the final regressions (with a minimum of 199 replications). Within-variation in BF percentage over time is very low. As a consequence, the preferred approach—fixed-effects models—has very low statistical power, leading to non-significant effects of BF with ambiguous meaning (see Table A3 in Supplementary Appendix A). Therefore, we report results from random-effects models. Due to the possibility of gender-specific effects of key explanatory variables and covariates, all models are estimated separately for women and men.

In a first step, we rule out human capital differences (within the bounds of observational data) by inspecting weight-specific differences in the following productivity variables: educational level (years of schooling), work experience (years of working full-time, working part-time, and being unemployed), and four dummy variables representing no vocational training, completed vocational training, masters of craftsmen, or university degree. Moreover, we test for weight-specific differences in intelligence using two ultra-short cognitive performance tasks, namely, the symbol digit task and the animal naming task (Lang *et al.*, 2007).[5] We also test for differences in occupations with or without representative tasks using a dummy variable for having an upper white-collar profession (based on the ISCO88 classification system). As health also influences productivity, we finally test for differences regarding general health (see Supplementary Appendix B for a discussion of the dynamic interplay between health and weight). To measure health, we use two indices for physical and mental conditions ranging from 0 to 100 (Andersen *et al.*, 2007), number of days absent from work (in the previous year), the number of doctor visits (in the previous 3 months), and the subjective perception of health on a scale from 0 to 10 (see Supplementary Appendix C for the detailed description of our operationalization).

Based on these analyses, we then chose the control variables for the second step of our statistical analyses: estimating the association of body composition with

Table 2. Random-effects models of BF and FFM for the log hourly wages

	Men			Women		
Log hourly wages	M_1	M_2	M_3	M_4	M_5	M_6
BF in kilograms	−0.005**	−0.002	−0.002	−0.011***	−0.008**	−0.009***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)	(0.003)
FFM in kilograms	0.007***	0.004**	0.004**	0.010*	0.009*	0.010*
	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)
Selected productivity variables		✓	✓		✓	✓
Additional productivity variables			✓			✓
Demographic variables	✓	✓	✓	✓	✓	✓
Variables used in interaction terms	✓	✓	✓	✓	✓	✓
$N_{observations}$	3,717	3,717	3,717	3,439	3,439	3,439
$N_{subjects}$	1,057	1,057	1,057	1,066	1,066	1,066
R^2 within	0.095	0.103	0.108	0.101	0.113	0.119
R^2 between	0.327	0.572	0.570	0.269	0.512	0.515
R^2 overall	0.282	0.486	0.492	0.251	0.448	0.450

Notes: BF and FFM in kilograms are centred around the mean in the random-effects models. All models (M_1–M_6) include demographic variables (parental education, federal states, dummy: German citizen, dummy: children under 16 living in the HH, dummy: interviewer present, waves) and variables used in the interaction models (Table 3: job change, job tenure, age). M_1 and M_4 are models without any productivity variables, M_2 and M_5 are the slender models with the selected productivity variables (education in years, dummy: master of craftsmen, dummy: no vocational training, years of working full-time and being unemployed, symbol digit task; animal naming task, dummy: upper white-collar profession, days absent, number of doctor visits, physical health composite scale, subjective health), and M_3 and M_6 are models with all productivity variables (dummy: university degree, dummy: vocational training, years of working part-time, mental health composite scale), dummy: self-doubts, dummy: being married. Standard errors in parentheses are bootstrapped and clustered around individuals.
$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

wages after controlling for all observed productivity differences. We suspect that more than human capital differences is at work only if weight effects remain after this covariate adjustment. This motivates the third step of our approach: adding interaction terms to empirically disentangle statistical and taste-based discrimination. As summarized in Table 1, the interaction terms include job change (in the previous year; dummy coding), job tenure (years of employment in the same company; continuous), and age (continuous). If weight-related statistical discrimination is present, we should find interactions of these indicators with body weight, whereas the absence of such would be in line with the presence of taste-based discrimination.

As derived from a theoretical analysis using directed acyclic graphs (for more details, see Supplementary Appendix B and Bozoyan and Wolbring, 2015), we additionally include the following covariates in all models: parental education (years of schooling), dummies for German citizenship, federal state, having children under 16 living in the household, panel waves, and the interviewer mode (for an overview of the descriptive statistics, see Table A4 in Supplementary Appendix A). Our final, unbalanced sample includes 3,717 observations for 1,057 men and 3,439 observations for 1,066 women.

Results

To test for potential correlations of body weight with productivity, we estimated 16 models with productivity variables as dependent variables and body composition as the treatment variable. It is important to note that we are not interested in causal effects but in associations at this point (see the section 'Some Notes on Causality and Endogeneity' in Supplementary Appendix B for a discussion of the complex temporal interplay). To provide an upper-bound estimate of weight-related productivity differences, we count differences that are at least significant at the 10 per cent level. Results for BF are summarized in Figure 2. The conditional effects plot shows that for men and women combined, 10 out of 16 productivity variables are significantly correlated with BF on at least a 10 per cent significance level regarding either men or women.

The association of years of schooling and body composition is significant for both men and women but is slightly stronger for men. BF also correlates positively with the probability of being a master of craftsmen and negatively with the likelihood of having no vocational training at all. Differences in employment history exist with respect to the total duration of unemployment for women, whereas working full-time only plays a role for men. We find an additional correlation with the type of

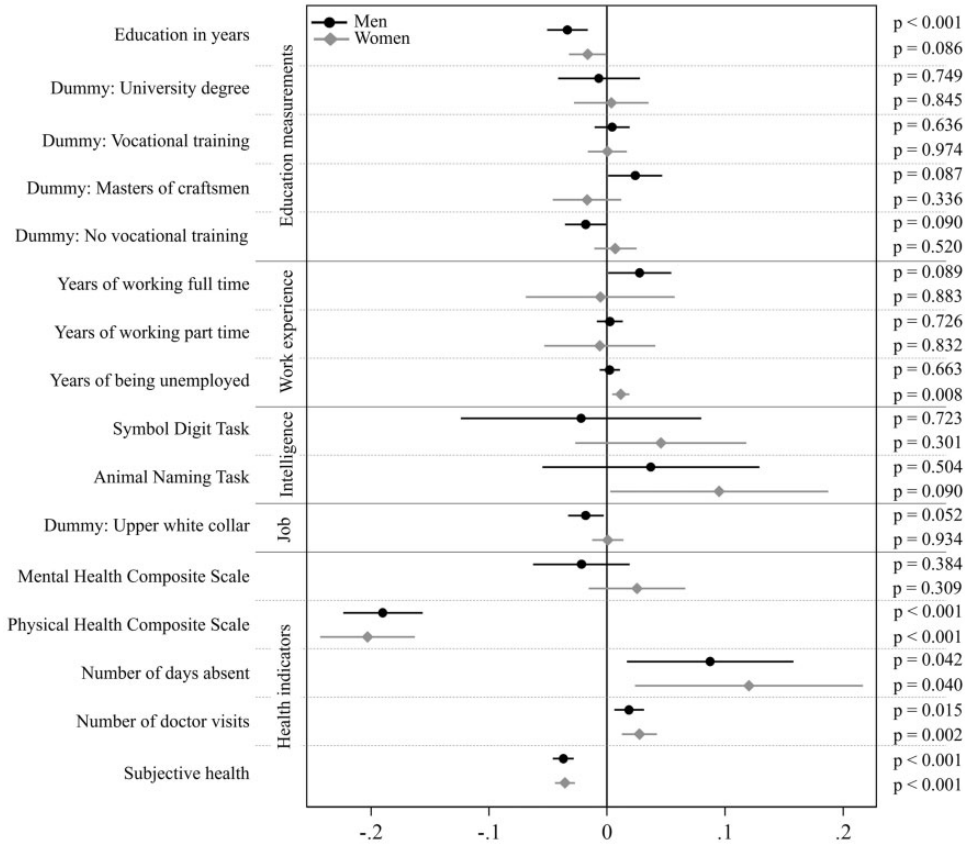

Figure 2. Conditional effects plot: productivity variables regressed on BF in kilograms

Notes: Simple pooled linear and logistic regressions. The horizontal axis shows the OLS coefficients and, in case of binary outcomes, the log odds of BF in kilograms with the 90 per cent confidence intervals as estimated from our data. All 16 models include the following control variables: age, social background, and duration of education (except the first model). Standard errors are bootstrapped and clustered around individuals. $N_{women} = 3{,}439$ and $N_{men} = 3{,}717$. An association between BF in kilograms and the following productivity variables exists for either men or women on at least a 10 per cent significance level: education, master of craftsmen, no vocational training, years working full-time, years of being unemployed, animal naming task, upper white-collar, physical health composite scale, number of days absent, number of doctor visits, and subjective health.

profession men have, but not for women. Finally, the most substantial weight-specific differences concern health indicators: BF significantly and strongly correlates with sick leave, subjective and objective (PHS) physical health, and the number of doctor visits for men as well as women.[6] The findings are similar for FFM, but the correlations are weaker in most instances and not always statistically significant.

In sum, we observe weight-related productivity differences, but they are less pronounced than widespread stereotypes and prejudices suggest. Nonetheless, results indicate that overweight and obese individuals are, on average, less productive according to some but not all dimensions under investigation. We conclude from this that human capital differences add to the overall picture of weight-related wage differences.

In a next step, we estimated random-effects models to ascertain whether there is a correlation of body composition with hourly wages after adjustment for the identified productivity differences (M_2 and M_5 in Table 2, and for the complete models with all controls listed, see Table A5 in Supplementary Appendix A).[7] As can be seen in Table 2, we only find significant associations of body composition with wages for women. Men do face a 'fat penalty' if productivity factors are not held constant (M_1). The disadvantage diminishes after controlling for education, work history, and health: Without productivity controls, a 10-kilogram increase in BF accounts for around 4.9 per cent of the hourly wage. If we add these controls to the model, a 10-kilogram increase in BF only accounts for 2.0 per cent of the hourly wage and the effect is no longer significant at a

10 per cent level. As can be seen in Table 2, the effect pattern goes in the opposite direction for FFM.

It therefore seems that for men, productivity is the most important explanation for fat-specific disadvantages. Women exhibit a different pattern: BF is strongly correlated with wages even after controlling for productivity factors. These effects are not only significant from a statistical but also from a substantive perspective: 10 kilograms of additional BF go hand in hand with an 8.0 percentage point lower wages. Although observational data make it impossible to completely rule out the possibility that other unobserved differences in productivity bring about these inequalities, the fact that wage differences for men vanish after covariate adjustment is a strong indication that we have captured the relevant confounders. To test the gender-specific differences between the models, we estimated a complete model including interaction terms of sex with all other variables, respectively (Table A6 in Supplementary Appendix A). Whereas the interaction effect between FFM and sex is not significant, the interaction term of BF and sex is significant at the 5 per cent level. We can therefore conclude that, most likely, women's wages are being affected by more than mere human capital differences.

To better understand whether *statistical discrimination, taste-based discrimination*, or both are additionally at work, we add three theoretically derived interaction effects to the regression models. All interaction terms are added in separate models to avoid unnecessary losses in statistical power due to multicollinearity (for a model containing all interaction terms simultaneously, see Table A7 in Supplementary Appendix A). As expected, we found no significant interaction effects for men (see Table A8 in Supplementary Appendix A). For women, we report results for interactions with BF here (Table 3) and results for interactions with FFM in Table A9 in Supplementary Appendix A. For men, the results for interactions with FFM can be found in Table A10 in Supplementary Appendix A. To further an intuitive understanding of the results, we also display these interactions graphically (Figure 3; Ai and Norton, 2003; Valentine *et al.*, 2015).

First, as mentioned earlier, according to theories of statistical discrimination, body composition should be more influential under circumstances characterized by large asymmetries in information, such as entering the labour market for the first time or starting a new job. In contrast, body composition should lose and productivity factors gain importance the longer an individual works for the same employer. As shown in Table 3, we find no significant interaction between BF and labour market entry or job change for women. This is a clear hint towards the presence of taste-based discrimination (Figure 3).

Table 3. Random-effects models of interaction terms with BF in kilograms for women

Log hourly wages	M_{7a}	M_{7b}	M_{7c}
BF in kilograms	−0.008**	−0.008**	−0.008**
	(0.003)	(0.003)	(0.003)
FFM in kilograms	0.009*	0.009*	0.009*
	(0.004)	(0.004)	(0.004)
Job changes	−0.059***	−0.058***	−0.058***
	(0.018)	(0.018)	(0.018)
Job tenure	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
Age	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)
Animal naming task	0.0003	0.0003	0.0003
	(0.001)	(0.001)	(0.001)
Symbol digit task	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
BF in kilograms × Job changes	−0.0005		
	(0.002)		
BF in kilograms × Job tenure		−0.00001	
		(0.0001)	
Animal naming task × Job tenure		0.0002*	
		(0.0001)	
Symbol digit task × Job tenure		−0.0001	
		(0.0001)	
BF in kilograms × Age			−0.0001
			(0.0001)
$N_{observations}$	3,439	3,439	3,439
$N_{subjects}$	1,066	1,066	1,066
R^2 within	0.1130	0.1150	0.1131
R^2 between	0.5116	0.5123	0.5119
R^2 overall	0.4483	0.4493	0.4481

Notes: All continuous variables used in interaction terms are centred around the mean (BF in kilograms, job tenure, age, animal naming task, and symbol digit task). All random-effects models include the selected productivity variables (education in years, dummy: master of craftsmen, dummy: no vocational training, years of working full-time and being unemployed, dummy: upper white-collar profession, days absent, number of doctor visits, physical health composite scale, subjective health), all main effects (BF in kilograms, dummy: job changes, job tenure, age, animal naming task, symbol digit task), and demographic variables (parental education, federal states, dummy: German citizen, dummy: children under 16 living in the HH, dummy: interviewer present, waves). Standard errors in parentheses are bootstrapped and clustered around individuals.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Based on a similar rationale, we next observe potential variations of the weight penalty by length of job tenure. Looking at Table 3 we can see, as expected, that the longer a woman works for the same employer, the stronger the association of intelligence (measured with the animal naming task) with hourly wages becomes (significant at the 5 per cent level). In contrast to theories of

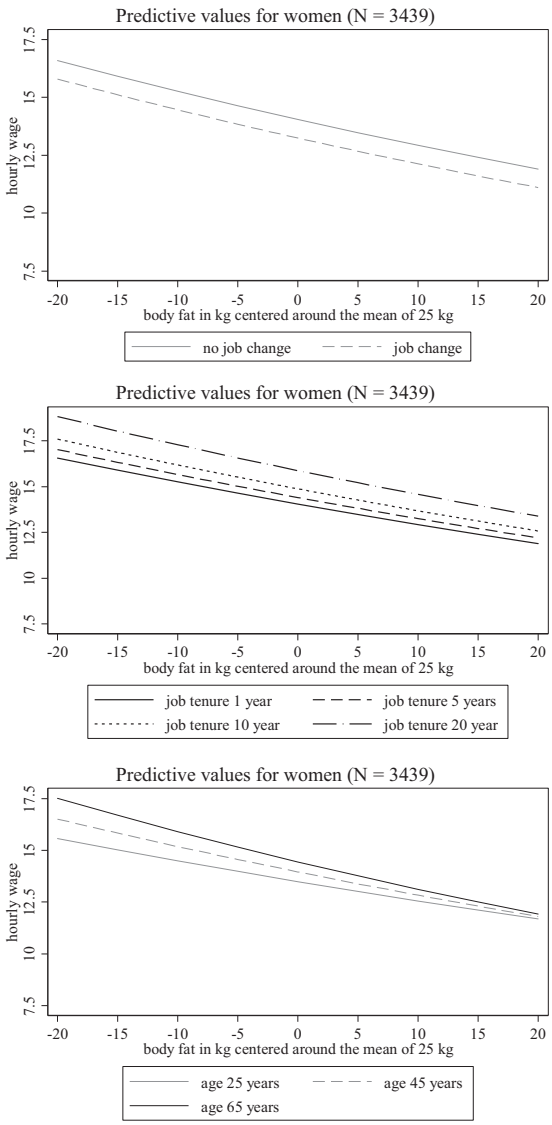

Figure 3. Interaction terms with BF—predictive values

Notes: All plots are derived from models M_{7a}, M_{7b}, and M_{7c} (Table 3). Please be aware that these predictive values are only approximately correct. To get the exact results, predictive values in a log model should be corrected by multiplying them with the anti-logged expected values of the error term (Cameron and Trivedi, 2009).

statistical discrimination, we observe that the effect of BF does not significantly vary by job tenure (Table 3 and Figure 3).[8] Therefore, we once again conclude that only taste-based discrimination is in line with these results.

Finally, we take the possibility of variation by employees' age into account. We anticipate a decline in statistical discrimination with an increase in age. Discrimination should be especially apparent for young workers, who lack previous work experience that signals ability. In contrast, according to the taste-based explanation, the weight-specific wage gap should be stable or could even widen over time due to an accumulation of inequalities and disadvantages over the life course. Figure 3 and Table 3 show that the interaction effect between age and body composition is very small and not significant.

Conclusions

Empirical studies have documented considerable differences in a variety of social outcomes between normal weight, overweight, and obese people. However, as has been repeatedly reproached in the literature on social stratification (Charles and Guryan, 2011; Diewald and Faist, 2011; Reskin, 2003), not much is known about the generative mechanisms that explain social inequalities and discrimination in more detail. In this article, we proposed a theory-driven *modus operandi* to gain insights into the causal pathways at work behind these phenomena. The centre of our approach is divided into two parts: First, we rule out productivity differences, and then explore interaction effects of social group membership with job change, duration of job tenure, and age. In this way we have attempted to empirically disentangle explanations based on human capital theory, statistical discrimination, and taste-based discrimination.

Our results for the German labour market indicate that performance-related variables such as education, work experience, occupation, and physical health almost fully explain fat-based differences in wages among men. Although variation in productivity also contributes to social stratification among women, body weight is still significantly and strongly correlated with women's wages after adjusting for skill indicators. All three investigated interaction effects thereby point to taste-based and not to statistical discrimination as the main driver of female wage inequalities. Differences in wages between normal weight, overweight, and obese employees do not decrease after job changes and also remain stable with increasing job tenure and age.

Wage inequalities, at least for women in the German labour market, are not just the consequence of differences in productivity or a lack of information but the result of discrimination. Hence, for practical measures to reduce weight-based discrimination of female employees, removing information asymmetries is insufficient. A more promising strategy would be to fight taste-based discrimination against the overweight and obese. As our results showed this type of discrimination against

women only, we likely contribute a further puzzle piece to the explanation of the German gender wage gap (for more details on the German gender wage gap, see Christofides *et al.*, 2013).

Obviously, the finding of weight-based discrimination of women, but not men, begs an explanation. Although not being able to provide a full explanation here, it appears likely that physical appearance is more important for the judgement of women due to gender roles. As Maralani and McKee (2017: p. 288) have recently emphasized, 'in the social world, "too fat" is a subjective, contingent, and fluid judgment that differs depending on who is being judged'. The existence of gender-specific expectations about physical appearance, stereotypes derived from body weight (e.g. wealth vs. laziness), as well as selection into occupations with a differing focus on physical attractiveness might help put our empirical findings into context.

To strengthen this argument, it would be particularly promising for future research to explore the role of gender-specific beauty norms (Hakim, 2010; Wolbring and Riordan, 2016) in shaping individual tastes. Against this background, comparing countries that systematically differ in the culturally assigned significance of male and female body weight as a factor in physical attractiveness might reveal additional insights into this topic. Furthermore, as our analysis showed no interaction of weight with job tenure or age, weight-related wage differentials seem to be established quite early in the life course. Thus, a detailed investigation of career entries appears to be another fruitful line of future research for a better understanding of the weight wage penalty.

Our study has faced several limitations. First, we had to rely on self-reported information regarding body height and weight to indirectly estimate BF and FFM instead of directly measuring them. This certainly reduced the precision of our effect estimates without introducing systematic bias. Second, although the use of the GSOEP enabled us to conduct a large-scale longitudinal analysis, due to low within-variation of body weight over time, we could not fully exploit the potential of panel data for causal inference, in particular dealing with unobserved heterogeneity and reverse causality (see Supplementary Appendix B for a more detailed discussion). The inability to apply fixed-effects estimations to control for time-constant influences of potential confounders is particularly regrettable, as the proposed method to more directly test for different mechanisms of discrimination shares strong assumptions about exogeneity with other approaches using observational data. Finally, we have only illustrated the method for the case of discrimination of the overweight and obese. However, the proposed approach is similarly applicable in other domains of stratification research. Thus, future research should also explore whether gender, race, and membership to other social groups interact in similar ways with job change, job tenure, and age as reported here for body weight.

Notes

1 BMI = weight in kg/(height in m)^2

2 See http://apps.who.int/gho/data/node.main.A900A?lang=en. Portions of both sexes are added and divided by 2.

3 A non-zero variance in productivity means that within a social group, some heterogeneity with respect to ability, skills, and performance exists. This is usually the case in reality. For example, it is very likely that some migrants have high education, whereas others have low education. As Aigner and Cain (1977) formally show, one implication from models of statistical discrimination in case of non-zero variance is that highly educated members of the ascriptive group are negatively discriminated, whereas poorly qualified group members are positively discriminated. Recently, Schaeffer and colleagues (2016) have provided supportive evidence for this contraintuitive hypothesis for the German labour market. They report that poorly qualified Turkish migrants receive higher wages than German individuals with similar educational credentials.

4 Labour market participation might be selective (especially for women), which might lead to sample selection bias. To address this possibility, we ran a dynamic selection correction as suggested by Wooldridge (1995) and applied by Gangl and Ziefle (2009). Although the results in Supplementary Appendix A show that both for men and women, labour market participation is indeed selective, our main findings concerning the weight wage penalty remain remarkably stable (Table A1 in Supplementary Appendix A).

5 Intelligence was collected in Wave 2006 and in Wave 2012 of the GSOEP. We conceptualized intelligence as a rather stable construct, and filled in missing values in the remaining waves as follows: 2002 and 2004 have the same values as 2006; 2008 and 2010 have the same values as 2012. The two tests, symbol digit and animal naming, were only collected within a subsample of the GSOEP, causing our sample to be further restricted by half (for more details, see Supplementary Appendix C).

6 We find no significant correlation between BF and university degree, vocational training, working part time, or

the mental health indicator for either men or women. For men, BF is also not associated with intelligence (according to our measurement). For women, the association is significant at the 10 per cent level, but in the opposite direction than stereotypes would predict.

7 In addition, we ran a full model (M_3 and M_6 in Table 2), but as the results are very similar, we focus on the slender model. We also tested for non-linear influences by adding squared terms of BF and FFM, but the squared terms turned out to be not significant, whereas the main effects (especially the effect of BF for women) remained the same.

8 One could argue that only the good matches survive having higher wages and tenure, which might bias our results (see also Dustmann and Pereira, 2008). We therefore estimated the same model only with those who experienced no job change since 2001 (the last year before the first sample wave). As we found no interaction effect between tenure and body composition but the main effects of body composition remain robust, we can be more certain that, even if only good matches survive, individuals with a higher body fat percentage are disadvantaged due to tasted-based discrimination. Further, it is possible that no individuals with high body fat percentages achieve high tenure. However, a short descriptive analysis shows that even if women have more than 30 kg of body fat, the mean tenure rests at 12 years and a maximum of nearly 42 years.

Supplementary Data

Supplementary data are available at *ESR* online.

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