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# Uncovering the Roots of Obesity-Based Wage Discrimination: The Role of Job Characteristics

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# ABSTRACT

## Uncovering the Roots of Obesity-Based Wage Discrimination: The Role of Job Characteristics*

This paper investigates the roots of labour market discrimination underlying the negative correlation between body fat percentage and wages. Using a large panel dataset of individuals drawn from the 1997 National Longitudinal Survey of Youth (NLSY97) for the US, we test whether residual wage gaps (once observed differences in productivity related to obesity are controlled for) are due to prejudice (taste-based discrimination) or statistical discrimination. Our main contribution is to examine how these two types of discrimination hinge on a wide range of obese individuals' specific job and occupational characteristics (drawn from the O * Net Online database). Our analysis sheds light on whether discrimination originates from the attitudes of clients, fellow-workers or employers. We find strong empirical evidence supporting taste-based discrimination against obese females, especially as they become older, in jobs requiring frequent communication with either clients or employers. The evidence on this issue for males is weaker. These differences may be explained both by an over-representation of males among employers and different image concerns against people of the same gender.

**JEL Classification:** J71, J15, J31

**Keywords:** obesity, wages, job characteristics, NLSY97, O*Net Online

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# 1. Introduction

How the prevalence and rise of obesity impinges on the population welfare and on economic growth has been the subject of an extensive literature (Philipson and Posner, 2003). Thus, a widely established fact in the medical literature is the existence of a strong causal relationship between excess body fat and a wide range of diseases (Chrostowska et al., 2013; Youssef et al., 2021). The economics literature in turns has long recognized the increasing impact of overweight/obesity on expenditures in health insurance and social security systems (Trasande and Chatterjee, 2009). This evidence has led the World Health Organization (WHO) tos declare growing obesity as one of the major health problems worldwide, and as a global epidemic since 1997 (Rohana, Chandrika and Upul, 2020).

In parallel with these developments, research on how wages and obesity are related has gained both scientific and media relevance.[1] In particular, a regular finding of this strand of the literature has been a negative association between obesity and female wages, mainly concentrated among white women, while the evidence is more ambiguous for men.[2] Nonetheless, there is no well-established consensus on the specific channels linking both outcomes for either gender. This paper aims at filling this gap.

**Related Literature Review**. Two early studies on this topic are Gortmaker et al. (1993) and Sargent & Blanchflower (1994). Their approach consists of regressing individual wages on a lagged value of a body weight measure (in addition to other controls) to guard against reverse causality, namely that low income leads to a poorer diet and worse physical condition (see Clark et al, 2020). Both studies find a negative and statistically significant relationship, particularly among women and not for men. A noticeable caveat, however, is that the use of lagged regressors does not necessarily preclude the potential

[1] Baum & Ford (2004) and Majumder (2013) examine this issue using data for the US (2016); Lin (2016) and Huang, Yabiku, Previos and Kronenfeld (2016) focus on Taiwan and China, respectively; Brunello and D`Hombres (2007) analyse an aggregate sample of EU countries, while Bozoyan & Wolbring (2011) and Greve (2008) study the country cases of Germany and Denmark, respectively.

[2] The distinction among whites, blacks, hispanics, and “other races” has only been made in the literature dealing with the US, where different results for these ethnic groups are found relevant (see Cawley, 2004; Majumder, 2013). Nonetheless, to avoid confusion with other sources of discrimination different from obesity, our focus here lies exclusively on white individuals of either gender.

existence of endogenous factors leading to some omitted variable bias (OVB). To overcome this limitation, Averett and Korenman (1996) propose to use the difference between the individual's body mass index (BMI) and that of a close relative as the relevant explanatory variable. Such a transformation would help eliminate the OVB caused by unobservable endogenous variables, such as genes shared between relatives or family habits that could affect weight.[3] Their main finding is the lack of any statistically significant relationship between wages and obesity for either gender, though this could be possibly due to their small sample sizes (about 800 couples). In the same vein, Pagan and Davila (1997) address the endogeneity problem using instrumental variables (such as family poverty level and health limitations, plus a self-esteem indicator), but a Hausman test rejects the validity of the instrument exclusion restriction.

In line with those studies, Cawley (2004) uses a similar estimation approach, this time implemented in a much larger sample drawn from the 1979 National Longitudinal Survey of Youth. Once again, a negative and significant relationship is found for white women, both when a (seven-year) lagged weight and the BMI difference with respect to a relative are chosen as regressors.[4] As regards black and Hispanic women, despite finding a negative correlation, their coefficents are smaller in absolute value than those of white women, and even lack statistical significance when the BMI-difference is used as the regressor of interest. Regarding men of any race, the estimated coefficients are either statistically insignificant or even slightly positive in the case of whites.

In turn, Baum and Ford (2004) analyse this issue using the same sample as Cawley's (2004), this time by means of a panel data model with individual fixed effects (FE) estimated in first-differences. Note, however, that this estimation method still fails to control for time-varying endogenous unobservables, such as motivation or psychological conditions (see Attila, 2008). As in the previous literature, they report a negative and significant impact of BMI on female wages which, however, is insignificant for men. Furthermore, they try to identify the channels behind this negative relationship for women by including interactions of the BMI with different proxies of job characteristics, health status of the individual, an indicatorvariable for employer-paid health insurance

[3] BMI = $\frac{Weight\ (kg)}{[Height\ (m)]^2}$

[4] Cawley (2004) also use an IV estimation approach to cater with the endogeneity of BMI but, as in Pagan & Davila (1997), the validity of their instruments is rejected.

and, finally, seniority in the company.[5] Among all these controls, only job experience turns out to be statistically significant, pointing to an adverse effect of obesity on wages as women get older. As for men, estimates are smaller and are only significant for jobs involving close contact with clients.

Within the line of research focusing on the channels linking fitness with wages, Bhattacharya and Bundorf (2009) are only able to find an obesity penalty among female employees whose health insurance is paid by the employer, which is attributed to higher health expenditures related to obesity among females than males. Neumark, Bank and Van Nort (1996) and Root (2009) address the identification of the roots of discrimination as regards physical appearance by exploring the relationship between physical beauty and the probability of being hired. Their findings, common to both genders, are that less attractive people are less likely to get hired. Lastly, Hamermesh & Biddle (1994) carry out a similar wage discrimination study, documenting again a beauty premium for both men and women irrespective of their specific occupation, which they attribute to pure taste discrimination from the employers' side.

More recently, DeBeaumont (2009) reports evidence in favour of higher obesity penalties in the US for women in sales-related occupations *vis-á-vis* those classified as "professional" or "administrative" staff which presumably involve less direct contact with clients. Han et al. (2009) adopt a similar approach, where the above-mendioned occupation categories are replaced by a set of non-cognitive skills required in various trades -- such as speaking in public, supervising, persuading, helping or serving. They conclude that most of these traits lack influence on the relationship between BMI and wages for men, while women happen to be penalized in those trades that require oral communication or serving. Hence, clients are pointed as a potential source of taste discrimination. Likewise, Moro et.al. (2019) fail to find empirical support about sorting of overweight people in the US into jobs that require little interaction with the public. Lastly, note that, while BMI has been widely used as a measure of obesity in the literature, a number of researchers and the WHO (1995) have argued that it might fail to distinguish body fat from non-fat body components where the former relates to obesity while the latter captures muscularity. As a result of these criticisms, Wada and Tekin (2010) and

[5] In Baum and Ford (2004) BMI is split into "low", "normal", "overweight" and "obese", following the above-mentioned WHO criteria.

Bozoyan and Wolbring (2011) have proposed body fat percentage (BFP) as an improved measure of obesity in their analysis of its association with wages in the US and Germany, respectively. Once again, these authors find the conventional negative estimates in OLS regressions but not in FE specifications. In later research, Bozoyan and Wolbring (2018) replace the FE by a random-effects (RE) estimation approach to on the grounds that time variation in variables like body fat and non-fat body mass is not large enough to justify the use of the FE. Using this time a German dataset, they find that obese women suffer from taste-based discrimination, whereas overweight and obese men earn less due to human capital differences.

**What this paper does**. Relying on the previous empirical evidence, our goal in this paper is to analyse how the origin of the obesity-wage penalty by gender relates to a wide range of job characteristics in different sectors. In particular, our approach helps shed light on whether clients, workmates, employers or suppliers are the sources of discriminatory practices. To do so we adopt the REs approach used by Bozoyan & Wolbring (2018), applied here to a large and rich sample of the US population drawn from the 1997 National Longitudinal Survey of Youth (NLSY97) which provides detailed information on a wide range of physical-fitness variable. In relation to the available literature, our main methodological contribution is twofold. First, we provide a much more detailed analysis of the heterogeneity of the impact of obesity on wages by gender. Second, we carry out a more thorough study of the origin of discrimination (statistical or taste-based) by focusing on the requirements and characteristics of each job. Specifically, to identify sources of discrimination due to prejudice, we consider a wider set of occupational characteristics than in previous studies on this topic (e.g. DeBeaumont, 2009, and Han et al., 2009), informing about direct contact with clients, employers or other economic agents outside the company. Some of these job characteristics turn out to be useful to rationalise some previously unexplained results in this literature.

Our most relevant findings can be summarised as follows. There is: (i) weak empirical support for wage discrimination among obese male workers, though some prejudice is found in jobs involving external communication with people outside the firm, like customers or suppliers, and (ii), stronger taste-based wage discrimination against female employees stemming mainly from clients and employers, which happens to be particularly relevant among older women in jobs involving higher responsibility and frequent oral communication. Thus, it seems likely that these gender differences in stereotypes could be explained by the existence of gender-specific expectations on how physical appearance matters for men and women. One potential explanation of these differences could be that men are overrepresented in managerial positions and they discriminate more against obese workers of the opposite gender in terms of image concerns. According to the US Bureau of Labor Statistics (BLS), slightly above 60% of managers were men during the sample under consideration.

The rest of the paper is structured as follows. Section 2 reviews the basic theoretical framework underlying the link between wage discrimination and obesity. Section 3 describes the database, as well as the set of variables used in the empirical section. Section 4 discusses the estimation strategy, while Section 5 presents the main findings. Finally, Section 6 draws conclusions. An Appendix provides information the mapping of occupational codes from O*Net Online to NLSY97.

# 2. Basic theoretical framework

### 2.1 Human capital, health status and wage discrimination

Following Bozoyan & Wolbring (2018), we propose a basic theoretical setup embedding the two conventional mechanisms through which dissimilarities in body composition may explain wage gaps: (i) differences in human capital, and (ii) discrimination.

Regarding human capital, the standard lesson to be drawn is that competitive firms seek to hire and promote the most productive workers by paying them their marginal productivity of labour. Therefore, insofar as obesity reduces workers' productivity through worse health conditions or physical performance, lower wages would be solely explained by observed productivity-related characteristics.

As a result, the persistence of wage gaps among individuals who exhibit different weight but identical productivity should be interpreted as a cost for discrimination incurred by consumers/employers which is transferred to the worker in the form of lower remuneration. In such instances, discrimination could be of two types:

-**Statistical discrimination**: it takes place in settings where the principal should assess the productivity of the agent without observing it directly. In this context of asymmetric information, the group of all obese individuals would be associated with undesirable characteristics -- such as laziness, poor self-control or lack of discipline--, leading to lower expected productivity on the part of the principal (Carr and Friedman, 2005). From these considerations it follows that, whenever the employer is able to observe the true productivity of the agent, obese workers' wages would converge to the same pay achieved by non-obese workers with the same levels of human capital.

A simple way to summarize the main implications of statistical discrimination is by means of the simple textbook treatment in Borjas (2020): under incomplete information wages are determined as a weighted average of the expected productivity score, $S$, gathered from a screening test on a given person and the score of the group to which the individual belongs, $\bar{S}$, so that

$$W = \alpha S + (1 - \alpha)\bar{S},$$

where $\alpha \in [0,1]$ is a weight which may differ according to physical appearance since e.g. productivity may be harder to predict for obese people. As Altonji and Pierret (2001) have argued, the weight $\alpha$ should be an increasing function of variables like age and job tenure. The insight is that employers should be able to learn much faster about the true productivity of more stable and senior workers because this learning investment process will be in their benefit.

-**Taste-based discrimination** (or pure prejudice): it is present whenever the degree of discrimination does not vanish as information on the productivity of the agent increases; its origin is traditionally attributed to discrimination due to *animus* (i.e. prejudice). Accordingly, the principal incurs a cost in dealing with obese agents regardless of their productivity or other characteristics. This kind of discrimination could be due to cultural reasons (social norms) or personal conceptions fully unrelated to the individual's economic performance.

**2.2 Origins of discrimination and their link with occupational characteristics**

In this section we distinguish two possible roots of discrimination, regardless of whether it is statistical or based on prejudice:

-**Employers and co-workers:** First, hiring decisions by discriminating employers are not based on the wage of obese workers, $W_o$, but rather on $W_o(1+d)$, where $d$ is Becker´(1957) discrimination coefficient. By contrast, employers take the wage of non-obese workers, $W_n$, as representative of their true cost. Hence, when both groups of workers are equally productive and all firms exert discrimination, the only way obese workers would find a job is by accepting a lower wage equal to $\frac{W_o}{1+d}$. Otherwise, if only a few firms discriminate, Becker´s well-known prediction is that they will be competed away by non-discriminating firms. Second, if the root of discrimination stems from co-workers in a given job, then the obesity penalty should only be found in those trades involving direct contact with fellow workers in the same establishment. Assuming perfect substitution between both groups of workers in production, employees disliking to work alongside obese workmates would react as if their wage is $W_n(1-d)$, instead of $W_n$. Thus, in a perfectly competitive market, where fair employers hire whichever workers are cheaper, employees´ discrimination would lead to workers´ job segregation but not to wage gaps. Yet, if firms view both types of workers as imperfect substitutes (for reasons beyond their productivity), there will be some integration of workforces, and non-obese workers will have to be compensated through higher wages than their fellow obese workers with the same skill. Since it is difficult to identify these roots of discrimination separately in the absence of audit or experimental studies, our empirical approach is to lump these two cases together and use different proxies to measure the degree and intensity of obese workers' relationship with other agents inside the firm.

-**Customers and other agents outside the company**: in this case, the wage penalty should only be present in those trades where the employee and its customers happen to be in close or frequent contact. In other words, consumers will base their demand of goods and services not on their actual price $p$ but on the higher price $p(1+d)$. If the firm is unable to segregate its workforce placing obese workers away from public view, they will end up experiencing a wage fall to compensate employers for the profit loss. Note that, in addition to clients, there could be other entities external to the firm that are susceptible of discriminating, such as regulators and suppliers for whom the same reasoning applies. As above, our approach relies on interacting measures of these types of relations with obesity to identify their role as roots of discrimination.

A potential shortcoming of the previous theoretical setup is its inability to identify the source of workers´ discrimination in highly competitive trades or in those subject to high client turnover.[6] In those instances it could be argued that non-prejudiced clients eager to learn about the agent's true productivity (thus eliminating statistical discriminator) may not be in contact with the worker long enough to adapt their previous beliefs. For example, in highly competitive retail markets with low product differentiation, prejudiced customers could opt for buying in alternative shops in which they would not have to interact with obese employees. By the same token, in other markets where buyers lack alternative suppliers, it could well happen that, given the nature of the goods or services purchased (e.g. a durable consumer good), there are no frequent contacts between employees and customers, preventing the acquisition of accurate information on the true workers' productivity. Unfortunately, the lack of information on client turnover in our dataset prevent us from addressing this problem although the wide set of occupational codes and industry dummies used in the empirical analysis could somewhat ameliorate this potential bias.

In light of the previous considerations, our goal is to study how the type of discrimination varies with the characteristics of the job (see below). As discussed above, the insight is that consumers and employers may not discriminate in the same way as their relationship with the worker is different. Another possibility to consider is that the pace at which statistical discrimination vanishes depends on whether customers or employers acquire further information. Differences may arise from the demand-price elasticity of the good/service in each sector. For instance, in sectors where this elasticity is high, consumers exerting statistical discrimination could invest less in learning about the true productivity of employees because they can satisfy their demand elsewhere; by contrast, those who discriminate by prejudice would keep their penalty invariant. Conversely, in monopolistic industries, one should expect that employers (knowing that sales will not be reduced) would exhibit a lower degree of statistical discrimination.

Finally, regarding the characteristics of obese people´s occupations, it is likely that employers´ statistical discrimination is higher in positions of greater responsibility as

[6] Staff in restaurants, customer services (receptionists) and taxi drivers are good examples of jobs with high customer turnover.

prior beliefs on the lower productivity of these people translate into greater potential losses for firms. The same reasoning applies to clients experiencing a higher dissatisfaction cost when services are poorly executed by employees.

# 3. Data and sample selection characteristics

### 3.1 Panel data: US NLSY97

Our sample consists of a balanced data panel made up of ten waves of surveys (from 2001 to 2011, excluding 2005) extracted from the 1997 National Longitudinal Survey of Youth (NLSY97), in which a total of 8,984 individuals residing in the US were interviewed annually between 1997 and 2011, and biannually between 2011 and 2017. Respondents remained the same in all rounds; hence the balanced nature of the panel. They are full-time or part-time time employees in the civil sector, born between 1980 and 1984, and therefore aged between 17 and 21 years old in the first round of this sample (2001) and between 27 and 31 in the last round (2011). We only consider white respondents to avoid other sources of discriminations based on race. Due to their alteration in body weight during pregnancy, pregnant women were excluded from the sample. Moreover, sample exclusion also applies to those individuals whose height is below 114 and above 213 cm and whose weight is outside the 31-180 kg range, and those under 18 years of age.[7] Finally, we exclude individuals for which there is no complete information for all the variables considered in the study. Finally, in line with the literature, our dependent variable is the individual’s hourly wage, which is capped at a maximum of $ 500 per hour.

After choosing these selection criteria, the panel has a total of 9,658 person-year observations for white men and 8,823 for white women, with 5.7 years of complete information per individual on average in both cases.

### 3.1 Proportion of body fat as input of physical condition

In line with the criticisms made by Burkhauser & Cawley (2008), Wada and Tekin (2010) and Bozoyan and Wolbring (2011, 2018) on the low representativeness of BMI as

[7] Analysing self-employed workers´ labour earnings would be an interesting approach to measure customers´ discrimination, which is left for future research.

a proxy for individuals' physical condition, we follow these authors in choosing the percentage of body fat (BFP) as the anthropometric explanatory variable of interest in the sequel. BFP is defined as the ratio between an individual body fat (BF onwards) and their total weight (measured in the same units).[8] Unfortunately, NLSY97 does not collect direct measures of BFP or BF, although it does include information on the individual's body weight, height, race and sex. To overcome this limitation and obtain an estimate of BFP, we follow the imputation methodology proposed by Burkhauser & Cawley (2008) and Wada & Tekin (2010) which works as follows. First, making use of an external health sample that includes clinical measures of BFP, a generalized predictive equation for BFP is generated by regressing this variable on the health survey anthropometric covariates that are also available in NLSY97-- such as height and weight (plus their squares, cubes and interaction terms), marital status, residence status, age or urban environment. Next, the estimated coefficients in the predictive equation are then applied to the corresponding regressors in our dataset. The external database in which these coefficients have been estimated is the Third National Health and Nutrition Examination Survey (NHANES III), a survey carried out in the US between 1988 and 1994 which reports BFP measures. The specification of the predictive equations for FFM follows those in Wada (2007), yielding $R^2s$ above 0.80 for each gender.[9]

### 3.2 Occupational characteristics: O*Net Online

To capture the degree of contact of the NLSY97 respondents with other people inside and outside their firms and the level of responsibility in each job, seven types of controls are considered: "Being in contact or working directly with the public" ($Cont\_Pub$), "Importance of working with clients or the public in the job" ($Imp\_Clients$), "Frequency with which workers have to speak in public" ($Speak\_Freq$), "Importance of communicating with supervisors or colleagues within the company" ($Comm\_Int$), "Importance of communicating with other people outside the company" ($Comm\_Ext$), "Consequences of making a mistake at work" ($Job\_Mistake$), and "Importance of using analytical thinking at work" ($Analy\_Think$). Each of these

[8] $BFP = \frac{Body\ Fat\ (kg)}{Body\ weigh\ \ (kg)}$

[9] As a limitation of this imputation procedure, it should be noted that the coefficients obtained in the NHANES III sample are estimated for a population between 7 and 45 years of age, which is a wider age range than the one used for our NLSY97 dataset.

variables, defined by as an index ranging from 0 to 100 (from less to more important), has been extracted from the O*Net Online database and mapped to the Census Occupation Codes 2002(COC 2002) available for each individual's occupation in the NLSY97 sample.[10] Further details on the mapping procedure are provided in the Appendix.

### 3.3 Control variables and descriptive statistics

As mentioned earlier, the NLSY97 collects a wide variety of data on respondents in terms of demographic, economic, health (including height and weight) and human capital status. Table 1 shows the main descriptive statistics of the variables considered in the subsequent empirical analysis.

Demographic controls include dummy variables for region of residence ($Northeast$, $Northcenter$, $West$ and $East$), urban environment of residence ($Urban$ equal to 1), marital status ($Married$ equal to 1), number of people under 18 years of age living in the household ($< 18\_Home$), age in years ($Age$) and its square, being a US native ($Native$ equal to 1) and years of education of the father and mother ($Years\_Ed\_Fath$ and $Years\_Ed\_Moth$, respectively).[11]

As for human capital controls, the following are considered here: years of tenure in the same firm ($Tenure$), moving to a different job in the interview year ($Job\_Ch$ equal to 1), total hours worked in all jobs held by a worker ($Total\_Hours\_Work$), occupied in a "white collar" profession ($White\_Collar$ equal to 1), college degree ($College$ equal to 1), some college ($Junior\_College$ equal to 1), having received job training at least once in your life ($Training$ equal to 1), years of full-time, part-time or unemployed employee ($Years\_FT$, $Years\_PT$ and $Years\_Unem$ respectively),[12] years of completed education ($Years\_Ed$), and the percentile obtained in the ASVAB cognitive test of mathematics and verbal in 1999 (ASVAB_p_1999).

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[10] The selection of the occupational characteristics described above relies on the Work Activities, Work Context and Work Style categories defined in O*Net (https://www.onetonline.org/).

[11] Parental years of education have been computed as the averages of the biological and the residential father and mother, respectively.

[12] A full-time worker (resp. part-time) is defined as someone who works on average at least 20 hours (resp. between 1 and 20 hours) a week during the interview year, while and an unemployed worker is somone who has worked less than 1 hour a week.

Next, the following variables are used as health controls: $Overall\_Health$ is an index from 1 to 5 on how individuals perceive their own health status ("1" corresponds to category "excellent", "5" to "terrible"), $Times\_Sick$ refers to how many times the individual suffered an injury or illness during the last year, and $Days\_Sick\_Pay$ is defined by the number of days of paid sick leave individuals took in the last year.

As already noted, the dependent variable in all regressions is the (logged) inflation-adjusted hourly wage ($lnW$), where US CPI data drawn from the World Bank database (base year: 2010) is used to deflate wages in each year of the sample.

As shown in Table 1, female respondents have a higher BFP than men (0.33 vs. 0.24), receive a lower (real) hourly wage (11.7 vs. 14.2), have a higher educational attainment, especially in terms of completing college degrees, and represent a higher share in white-collar jobs. According to WHO (1995), BFP greater than 0.25 (0.33) defines obsesity for men (resp. women) aged 20-39, while those within the range 0.21-0.25 (0.31-0.33) represent borderline cases. Note that the above average figures in our NLSY97 sample may look seemingly high. Yet, we argue that they seem plausible because the average BFP for the whole adult US population which is even higher, i.e. 0.28 for men and 0.40 for women (see St-Onge, 2013), and obesity tends to be lower among younger individuals. As regards occupational characteristics, women have higher contacts with clients and other agents external to the firm, while their job mistakes are thought to have more serious consequences than males´.

| Table 1. NLSY79 sample descriptives | | | | |
|---|---|---|---|---|
| | White men | | White women | |
| | **Mean** | **S.E.** | **Mean** | **S.E.** |
| **Variables of interest** | | | | |
| BFP | 0.238 | 0.046 | 0.328 | 0.067 |
| Hourly (real) wage ($) | 14.245 | 21.191 | 11.705 | 14.097 |
| **Demographic controls** | | | | |
| Northeast | 0.192 | 0.394 | 0.178 | 0.383 |
| Northcenter | 0.325 | .468 | .299 | .458 |
| West | 0.197 | 0.398 | 0.211 | 0.408 |
| South | 0.286 | 0.452 | 0.312 | 0.463 |
| Urban | 0.732 | 0.444 | 0.741 | 0.439 |
| Native | 0.979 | 0.144 | 0.974 | 0.158 |
| Married | 0.203 | 0.402 | 0.255 | 0.436 |
| <18_Home | 0.563 | 0.921 | 0.677 | 1.011 |
| Age | 23.867 | 3.616 | 23.787 | 3.605 |
| Years_Educ_Fath | 12.056 | 4.449 | 11.928 | 4.567 |
| Years-Educ_Moth | 13.048 | 3.186 | 13.085 | 3.293 |
| **Human capital controls** | | | | |
| Tenure | 0.530 | 0.581 | 0.487 | 0.511 |
| Job_Ch (%) | 0.127 | 0.333 | 0.165 | 0.371 |
| Years_Ed | 13.220 | 2.458 | 13.829 | 2.461 |
| Training | 0.443 | 0.497 | 0.423 | 0.494 |
| College | 0.163 | 0.369 | 0.229 | 0.423 |
| Junior_College | 0.051 | 0.221 | 0.060 | 0.237 |
| Years_FT | 3.955 | 3.381 | 3.473 | 3.121 |
| Years_PT | 3.536 | 2.095 | 3.734 | 2.115 |
| Years_Unem | 3.279 | 2.065 | 3.455 | 2.003 |
| WhiteCollar | 0.205 | 0.404 | 0.379 | 0.485 |
| Total_Hours_Work | 11728.6 | 8387.3 | 10030.7 | 7009.5 |
| ASVAB_p_1999 | 57309.5 | 28324.6 | 60522.8 | 25692.3 |
| **Health status controls** | | | | |
| Days_Sick_Pay | 3.602 | 23.228 | 3.581 | 20.955 |
| Times_Sick | 1.382 | 1.025 | 1.781 | 1.387 |
| Overall_Health | 2.024 | .888 | 2.13 | 0.880 |
| **Occupacional controls** | | | | |
| Cont_Pub | 53.204 | 21.012 | 63.711 | 19.191 |
| Imp_Clients | 63.463 | 19.902 | 72.616 | 15.079 |
| Speak_Freq | 28.343 | 17.808 | 30.243 | 16.558 |
| Ext_Comm | 53.312 | 17.048 | 58.213 | 16.066 |
| Int_Comm | 70.531 | 11.077 | 73.946 | 10.254 |
| Job_Mistake | 47.892 | 16.8 | 41.066 | 17.697 |
| Analytic_Think | 63.177 | 14.394 | 64.505 | 12.517 |

*Note*: For the meaning of the acronyms in column 1, see subsection 3.3 above

## 4. Empirical strategy

### 4.1 Human capital, health and occupational controls

Our empirical strategy proceeds in three steps. First, as is conventional in the literature, we seek to capture which part of the association between hourly real wages and BFP is explained by differences in demographic characteristics related to productivity. Thus, we initially estimate a regression of the (logged) real hourly wage, $lnW$, of individual $i$ in period $t$ on the variable of interest, BFP, plus the set of demographic controls ($DemC\_it$) listed above and industry (13) and year-time effects ($Ind_s$ ,$Year\_t$). Next, to reduce OVB, this regression is augmented with the controls for human capital ($HKC\_it$), health ($HealthC\_it$) and occupational characteristics ($OccC\_it$). Some of these latter controls could be arguably endogenous. Nonetheless, as an accounting exercise, it is useful to know the extent to which the obesity gap can be explained by them since they also affect productivity. Accordingly, once we control for all the previous covariates, any persistent effect of BFP on wages could be attributed to discrimination. Specifically, the estimated regression models at the first stage are as follows:

$$lnW_{it} = \beta_0 + \beta_1 * BFP_{it} + \beta_d * DemC_{it} + \beta_s * Ind_s + \beta_y * Year_t + e_{it}, \qquad (1)$$

$$\begin{aligned} lnW_{it} = \; & Controls\ in\ (1) + \beta_k * HKC_{it} + \beta_h * HlthC_{it} \\ & + \beta_{oc} * OccuC_{it} + e_{it} \end{aligned} \qquad (2)$$

### 4.2 Disentangling statistical from taste-based discrimination

At the second stage**,** we proceed to identify the type of discrimination left after the first- stage regressions. For this purpose, we run separate regressions similar to (2), adding as further controls the interactions of BFP with three discrimination-indicator proxies captured by: (i) experiencing a job change during the year before the interview ($JobCh$), (ii) age ($Age$) and (iii) work seniority ($Tenure$). Grouping these three variables under the label $DiscI$, the following regression is considered,

$$lnW_{it} = \beta_0 + \beta_1 * BFP_{it} + \beta_2 * (BFP_i * DiscI_{it}) + Controls\ in\ (2) + e_{it} \qquad (3)$$

The insight for including these interaction terms in (3) is as follows. On the one hand, if statistical discrimination is present, the conjecture is that those individuals who recently changed jobs would have less time than stayers to prove their true productivity to their new employers. Thus, the coefficient $\beta_2$ on the interaction of BFP with $JobCh$ should be negative under statistical discrimination. Conversely, if this coefficient turns out to be positive and significant, discrimination should be interpreted as nepotism in favour of obese workers and, if insignificant, as discrimination based on prejudice. On the other hand, those individuals who are older and have accumulated longer tenure are likely to have provided solid information about their genuine productivity (in the form of a longer resumé, recommendations or recognition within the sector), and so they are less likely to experience statistical discrimination. Thus, we would expect to find positive and significant $\beta_2$ coefficients on the interactions of BFP with $Age$ and $Tenure$, reducing the negative effect of BFP on hourly wages (captured by $\beta_1$); otherwise the right interpretation would be discrimination due to taste in both scenarios. Table 2 summarises the interpretation of discrimination roots according to the signs of the $\beta_2$ coefficients on the interaction terms of BFP with the three above-mentioned controls.

**Table 2: Interpretation of $\beta_2$ coefficients on interactions terms with BFP**

| Interaction of BFP with/ | Positive & significant | Negative & significant | Not significant |
|---|---|---|---|
| **Age** | Statistical | Taste-based | Taste-based |
| **Tenure** | Statistical | Taste-based | Taste-based |
| **Job Change** | Positive Disc. | Statistical | Taste-based |

*Note*: The $\beta_2$ coefficient corresponds to the interaction between BFP and DIscI in equation (3) above.

Regarding the role of occupations, we add interactions of BFP with each of the indices of characteristics of the sector, again in separate regressions by like (2) above. As before, the sign and statistical significance of their estimated coefficients help evaluate whether a given occupational characteristic increases or reduces the obesity wage penalty. In addition, to reduce OVB, all these regressions include the full set of controls related to employment characteristics.

### 4.3 Discrimination and occupational features: triple interactions

At the third and final stage, we analyse the link between the type of discrimination and job characteristics. To carry out this exercise, a triple interaction specification is used between BFP, the type of discrimination indicators ($JobCh$, $Age$ and $Tenure$; jointly labelled $DiscI$) plus the significant occupational characteristics selected at the second stage. As before, the analysis is carried out in separate regressions for each type of discrimination indicator and job characteristic:

$$lnW_{it} = \beta_0 + \beta_1 * BFP_{it} + \beta_2 * (BFP_{it} * DiscI_{it}) + \beta_3 * (BFP_{it} * OccI_{it}) + \beta_4 * (DiscI_{it} * OccI_{it}) + \beta_5 (BFP_{it} * DiscI_{it} * OccI_{it}) + \beta_d * DemC_{it} + \beta_k * HKC_{it} + \beta_h * HlthC_{it} + \beta_{oc} * OccI_{it} + \beta_y * Year_t + e_{it} \quad (4)$$

Omitting the $it$ subscripts for simplicity in (4), it follows that

$$\frac{\partial}{\partial DiscI}\left(\frac{\partial\, lnW}{\partial BFP}\right) = \beta_2 + \beta_5 * OccI.$$

This means that, as the discrimination indicator varies, the change in the semi-elasticity of the wage with respect to BFP depends on the level of the occupational variable $OccI$, with the coefficients $\beta_2$ and $\beta_5$ determining the sign and slope of this change. If both coefficients were statistically significant and shared the same sign ( or if only $\beta_5$ is significant), the level of $OccI$ will only modify the semi-elasticity indicator upwards or downwards. However, if they exhibit opposite signs, there would be a cut-off level in $OccI$ above or below which the direction of the above-mentioned effect would be different, provided that the threshold value falls in the range between 0 and 100 (minimum and maximum values of all occupational variables). When the discrimination indicators correspond to "$Age$" or "$Tenure$", such thresholds would imply statistical discrimination for values of $OccI$ below them and, conversely, would point to prejudice for higher values. On the contrary, when considering the " $JobC$h" indicator, opposite signs of $\beta_5$ would point to statistical discrimination for values below the $OccI$ threshold and to positive discrimination for values above it.

### 4.4 Random effects estimation

### 5.3 Taste-based discrimination: the role of occupational characteristics

The estimation procedure applied to all the above-mentioned regressions (separately for men and women) is Random Effects-Generalized Least Squares (RE-GLS), according to the following panel-data regression model.[13]

$$y_{it} - \lambda * \frac{\sum y_{it}{}_{t=0}^{T}}{T} = \beta_0 + \beta_k * \left(X_{kit} - \lambda * \frac{\sum X_{kit}{}_{t=0}^{T}}{T}\right) + \left(v_{it} - \lambda * \frac{\sum v_{it}{}_{t=0}^{T}}{T}\right) \quad (5)$$

where $v_{it} = u_{it} + \mu_i$ and $\lambda$ is a quasi-time demeaning value defined as $\lambda = 1 - \frac{\sigma_u}{\sqrt{T\sigma_\mu^2 + \sigma_u^2}}$.

As is well known, the standard assumption in this model is that the controls are strictly exogenous w.r.t. the error term, $u_{it}$, and the individual fixed (unobservable) factors, $\mu_i$, such as intelligence, genes or time preferences. Otherwise, RE-GLS yields biased estimates. Our claim is that including a wide set of demographic, human capital, health and occupational characteristics controls in (4) could substantially reduce OVB in the coefficient on BFP by restricting the range of potential unobservables. Nonetheless, lacking a good instrument, the possibility of reverse causality (whereby wages could influence BFP instead of the other way around) cannot be discarded. To check this possibility, we follow Wada (2008) in using height as an IV in RE-2SLS (see Johi and Wooldridge, 2019) since most of adult height is reached by the end of one's teenage years, and therefore could be considered as a pre-labour market factor.[14]

# 5. RESULTS

### 5.1 Productivity and occupational characteristics.

Table 3 shows the results of the first-stage regressions (1) and (2) for men and women. As can be seen in columns (II) and (IV), adding the second set of controls modifies the BFP coefficient in the basic regression (1) (reported in columns (I) and (III)) in the same direction for both genders. With regard to men, the BFP coefficient is positive,

[13] Following Bozoyan and Wolbring, (2011), the justification to discard FE estimation is the low time-variation of BFP in our sample.

[14] Alternative instruments could be parents´ BFP which is available in NLSY97. However, the large number of non-respondents in the survey prevent us to use such IVs.

but not statistically significant in either specification. As a result, this preliminary empirical evidence does not yield support for any type of discrimination against males. As for women, the wage obesity gap becomes smaller once the extra controls are included, but the effect of BFP on wages is still negative and statistically significant at 5%. Without these controls, an increase of a standard deviation of the BFP (0.0672) implies a reduction of 2.5% (=-0.0672x 0.375) in female wages while, with additional controls, the wage loss declines to 2%. In line with the arguments above, the (residual) female obesity wage penalty could be attributed to discrimination.

**Table 3: Estimates of coefficients on BFP with different sets of controls**

| | Men | | Women | |
|---|---|---|---|---|
| **Dep. var: *LnW*** | **(I)** | **(II)** | **(III)** | **(IV)** |
| BFP | 0.175 | 0.121 | -0.375*** | -0.302*** |
| | (0.225) | (0.204) | (0.087) | (0.105) |
| DemC | **Yes** | **Yes** | **Yes** | **Yes** |
| HKC, HlthC & OccC | **No** | **Yes** | **No** | **Yes** |
| $N_{Obs}$ | 9658 | 9658 | 8823 | 8823 |
| $N_{Ind.}$ | 1684 | 1684 | 1554 | 1554 |
| $R^2$ within | 0.296 | 0.335 | 0.328 | 0.404 |
| $R^2$ overall | 0.260 | 0.333 | 0.278 | 0.413 |
| $R^2$ between | 0.257 | 0.374 | 0.223 | 0.408 |

*Note:* RE-GLS estimation. All columns include industry and year dummies. Robust standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01.

While the previous results correspond to RE-GLS estimation, Table 4 compares the estimates in columns II and (III) in Table 3 (reproduced again for convenience) with the RE-2SLS estimates, using height as an instrument for BFP (see subsection 5.3 above). As can be observed, at the cost of some efficiency, this comparison yields largely robust results as regards the obesity wage penalty by gender. Hence, the potential presence of reverse causality does not seem to be a big issue and, in the sequel, only RE-GLS estimates will be reported.

**Table 4: Comparison of coefficients on BFP estimated by RE-GLS and RE-2SLS**

| *Dep. var: LnW* | Men | | Women | |
|---|---|---|---|---|
| | **RE-GLS** | **RE-2SLS** | **RE-GLS** | **RE-2SLS** |
| BFP | 0.121 | 0.102 | -0.267*** | -0.244* |
| | (0.204) | (0.288) | (0.105) | (0.139) |

*Note:* RE-GLS estimation and RE-2SLS with height as IV. All columns include demographic, human capital, health, ocuupational controls and industry and year dummies. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 5 in turn reports the estimated coefficients on the double interactions of BFP with occupational indicators related to inter-personal communication with internal and external agents in separate regressions like (3). Contrary to the evidence obtained in the previous stage, the results now yield a significant wage penalty for obese male workers in those occupations involving intense direct contact with the public (at 5% significance level), consumers and external coomunication (at 10%). As regards women, the results are much stronger: the penalty is statistically significant in occupations involving close direct contact with the public ($Cont\_Pub$), clients ($Imp\_Clients$), frequent oral communication ($Freq\_Com$) and where mistakes imply serious consequences for firms ($Job\_Mistake$). Particularly noteworthy is the penalization of obese women who have to speak in public and deal with clients, but not for those communicatiing with outsiders, as it was the case for men. This result points to a very specific niche of job environments in which prejudice against obese women occurs, more closely related to the action itself of speaking in public rather than to dealing with clients.

Han et al. (2009) report similar results for women, taking the requirement of oral communication at work as the main job characteristic, but not necessarily with the public. However, while the characteristic of "serving"is the only one which is negative and significant in their study, our findings that intensive trades in direct contact with clients or the general public have significant effects extend theirs.[15] Finally, another novel

[15] Recall, however, that the NLSY79 sample used by Han et al. (2009) is not fully comparable to ours since it includes older people than those considered in our sample.

**Table 5: Estimates of coefficients on interactions of BFP with occupational characteristics**

| Interaction of BFP with/ | Men | Women |
|---|---|---|
| Cont_Public | -0.0127**<br>(0.0063) | -0.0137*<br>(0.0071) |
| Ext_Comm | -0.0200*<br>(0.0105) | -0.0073<br>(0.0069) |
| Int_Comm | 0.00286<br>(0.0152) | 0.0012<br>(0.0112) |
| Speak_Freq | 0.0111<br>(0.0097) | -0.0232***<br>(0.0068) |
| Imp_Clients | -0.0143*<br>(0.0084) | -0.0097***<br>(0.0036) |
| Analy_Think | 0.0041<br>(0.0113) | -0.0054<br>(0.0097) |
| Job_Mistake | 0.0028<br>(0.0092) | -0.0209***<br>(0.0068) |

*Note:* RE_GLS estimation with $lnW$ as the dependent variable. Separate regressions are run for each interaction term by gender. The definition of the acronyms for each reported interaction term with BFP can be found in subsection 3.3. All columns include demographic, human capital, health status, occupational characteristic controls and industry and year dummies for each survey observation. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

finding to highlight is the growing wage penalty related to making mistakes in the workplace, which is significant at 1% for women but not significant for men.

Summing up, although the previous results do not allow us to conclude that one gender is more discriminated than the other when working in front of the public, the penalty on making mistakes and on oral communication possibly implies that obese women could be worse treated than men in positions of higher responsibility, where these actions are bound to be more frequent.

### 5.2 Types of discrimination

Table 6 shows the estimated coefficients of the BFP interactions with the discrimination indicators ($DicsI$). In the case of men, none of them interactions is significant in line with the previous evidence on lack of discrimination. By contrast, the estimated coefficient on the interaction of female BFP with $Tenure$ is negative and significant, which provide support in favour of taste-based discrimination (and, conversely, against statistical discrimination which would yield a positive coefficient). For example, evaluating female tenure at its mean value (0.49 years) in column VI, an increase in BFP of one s.d. (0.0672) yields an obesity penalty of 2.8% (i.e., (0.286+0.249x0.49)x0.0672), which is 0.8 pp. higher than the 2% effect reported ealier (see Table 2) in the absence of this interaction term. Interestingly, the negative coefficient on the interaction of BFP with $Age$ indicates that the older a woman, the greater the penalty for being obese, implying a clear signal of prejudice. This result is especially striking given that the eldest women in our sample are at most 31 years old.

Finally, as an alternative approach to identify statistical discrimination, we test whether the relationship between BFP and $Job\_Ch$ is more relevant for younger individuals who have short work experience (and, therefore, for whom employers have less information about their productivity) than for older/more experienced workers. This test is implemented through separate regressions for workers aged 17-21 and 27-31 where a triple interaction among BFP, $JobCh$ and either $Age$ or $Tenure.$ Though not reported here to save space, these estimates are never significant, again providing support against statistical discrimination.

**Table 6: Estimates of coefficients on interactions of BFP with discrimination indicators**

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| **Dep.var: $lnW$** | **(I)** | **(II)** | **(III)** | **(IV)** | **(V)** | **(VI)** |
| BFP | 0.116 | 0.112 | 0.103 | -0.305** | -0.328** | -0.286* |
| | (0.208) | (0.106) | (0.206) | (0.135) | (0.162) | (0.161) |
| Age | 0.0158* | 0.0181* | 0.0158* | 0.0040 | 0.0222 | 0.00399 |
| | (0.0089) | (0.0939) | (0.0089) | (0.0091) | (0.0136) | (0.00912) |
| Tenure | 0.0316*** | 0.0314*** | 0.0221*** | 0.0356*** | 0.0350*** | 0.0742** |
| | (0.0095) | (0.0095) | (0.0072) | (0.0087) | (0.0089) | (0.0083) |
| JobCh | 0.00743 | 0.0155 | 0.0157 | -0.0469 | -0.0399** | -0.0409** |
| | (0.0958) | (0.0201) | (0.0207) | (0.0927) | (0.0172) | (0.0168) |
| BFP * JobCh | 0.0352 | | | 0.0191 | | |
| | (0.0405) | | | (0.0279) | | |
| BFP * Age | | -0.0344 | | | -0.0455* | |
| | | (0.0461) | | | (0.0221) | |
| BFP * Tenure | | | 0.1723 | | | -0.2487** |
| | | | (0.1641) | | | (0.1237) |
| $N_{Obs.}$ | 9658 | 9658 | 9658 | 8823 | 8823 | 8823 |
| $N_{Ind.}$ | 1684 | 1684 | 1684 | 1554 | 1554 | 1554 |
| $R^2$ within | 0.335 | 0.335 | 0.335 | 0.404 | 0.404 | 0.404 |
| $R^2$ overall | 0.333 | 0.333 | 0.333 | 0.413 | 0.414 | 0.413 |
| $R^2$ between | 0.374 | 0.374 | 0.374 | 0.408 | 0.408 | 0.408 |

*Note:* RE_GLS estimation with lnW as the dependent variable. Separate regressions are run for each interaction term by gender. The definition of the acronyms for each reported interaction term with BFP can be found in subsection 3.2. All columns include demographic, human capital, health status, occupational characteristic controls and industry and year dummies for each survey observation. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.7

### 5.3. Taste-basd discrimination: The role of occupational characteristics

Tables 7 (men) and 8 (women) display the results of the last-stage regressions including triple interactions of BFP with $Tenure$ (i.e. the most relevant $DiscI$ covariate in Table 5) and those occupational variables whose coefficients turned out to be most significant in Table 4 ($Exter\_Comm$, $Cont\_Public$ and $Imp\_Cons$ for males, and the last two indicators plus $Speak\_Freq$ and $Job\_Mistake$ for females). As can be inspected, the estimates of the $\beta_5$ coefficients on the triple interactions are statistically significant in most cases. Yet, in contrast to the results Table 5, the $\beta_2$ coefficients on the double interaction of BFP with the occupational covariates are hardly significant in any of these augmented regressions, implying that the relationship between BFP and these variables depends exclusively on those indicators which help identify type of discrimination.

**Table 7: Estimates of coefficients in regressions with triple interactions (Men)**

| **Dep. var: $lnW$** | **(I)** | **(II)** | **(III)** |
|---|---|---|---|
| BFP | 0.145 | 0.122 | 0.143 |
| | (0.198) | (0.126) | (0.182) |
| BFP * Tenure | 0.202 | 0.179 | 0.154 |
| | (0.173) | (0.192) | (0.167) |
| BFP* DiscI | -0.0086 | -0.0063 | -0.0055 |
| | (0.0067) | (0.0077) | (0.0082) |
| BFP * Tenure * Ext_Comm | -0.0061** | | |
| | (0.0028) | | |
| BFP * Tenure * Cont_Pub | | -0.0029 | |
| | | (0.0020) | |
| BFP *Tenure* Imp_Clients | | | -0.0022 |
| | | | (0.0016) |
| $N_{Obs.}$ | 9658 | 9658 | 9658 |
| $N_{Ind}$ | 1684 | 1684 | 1684 |
| $R^2$ within | 0.336 | 0.336 | 0.335 |
| $R^2$ overall | 0.335 | 0.333 | 0.334 |
| $R^2$ between | 0.377 | 0.374 | 0.376 |

*Note:* RE-GLS estimation with $\ln W$ as the dependent variable. The definition of the acronyms for each reported interaction term with BFP and Age can be found in subsection 3.3. Apart from the triple interaction terms, all columns include demographic, human capital, health status, occupational characteristic controls, industry and year dummies, and double interactions. Label DiscI in the interaction tem in the third row represents the specific component of the set of discrimination proxies considered in each of the three columns. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

**Table 8: Estimates of coefficients in regressions with triple interactions (Women)**

| Dep. var: $lnW$ | (I) | (II) | (III) | (IV) |
|---|---|---|---|---|
| BFP | -0.201** | -0.185** | -0.187** | -0.180** |
| | (0.093) | (0.087) | (0.096) | (0.089) |
| BFP * Tenure | -0.188** | -0.177** | -0.207*** | -0.182** |
| | (0.091) | (0.085) | (0.077) | (0.090) |
| BFP* DiscI | -0.0076 | -0.0132* | -0.0087 | -0.0065 |
| | (0.0089) | (0.0072) | (0.0074) | (0.0068) |
| BFP* Tenure* Job_Mistake | -0.0036** | | | |
| | (0.0018) | | | |
| BFP * Tenure* Speak_Freq | | -0.0052** | | |
| | | (0.0023) | | |
| BFP * Tenure* Cont_Public | | | -0.0012 | |
| | | | (0.0018) | |
| BFP * Tenure* Imp_Clients | | | | -0.0036** |
| | | | | (0.0017) |
| $N_{Obs.}$ | 8823 | 8823 | 8823 | 8823 |
| $N_{Ind.}$ | 1554 | 1554 | 1154 | 1154 |
| $R^2$ within | 0.408 | 0.405 | 0.423 | 0.406 |
| $R^2$ overall | 0.416 | 0.413 | 0.420 | 0.418 |
| $R^2$ between | 0.410 | 0.406 | 0.415 | 0.426 |

*Note:* RE-GLS estimation with $lnW$ as the dependent variable. The definition of the acronyms for each reported interaction term of BFP with tenure and DiscI can be found in subsection 3.3. Apart from the triple interaction terms, all specifications include demographic, human capital, health status, occupational characteristic controls, sector, industry and year dummies, and double interactions. Label DiscI in the interaction term shown in the third row represents the specific component of the set of discrimination proxies considered in each of the four columns. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

In the case of men, out of their three relevant occupational characteristics, only $Ext\_Comm$ leads to a greater penalty for BFP as tenure increases. This result indicates that the weak empirical evidence on taste-based discrimination against men is only related to those occupations that involve dealing with external agents, rather than customers or employers. For example, when $Tenure$ and $Ext\_Comm$ are evaluated at their sample means (0.53 and 53.3, respectively) and the coefficients on the insignificant regressors are restricted to be zero, the estimated coefficient on the triple interaction in column (I) of Table 6 implies that a one s.e. increase in BFP (0.046) is associated to a reduction of 0.8 pp. in the hourly wages of obese workers in close contact with customers.

In stark contrast to men, the estimates on the double interaction of female BFP and $Tenure$ remains negative and significant, though the size of its coefficient is smaller than in Table 5. As for the triple interaction terms, only the estimated coefficient on the interaction of BFP with $Tenure$ and $Cont\_Pub$ is insignificant while the remaining three interactions exhibit highly significant coefficients. For instance, using the significant coefficients in column (VI) and evaluating $Tenure$ and $Imp\_Cons$ at their sample means (0.487 and 72.6, respectively) implies that an increase of one s.e. in BFP is associated with a 2.6 pp. reduction in hourly wages where the contribution of the triple interaction is 0.8 pp, namely 30 percent of the total effect. Overall, we interpret this evidence as clearly supporting that customers and other internal agents are the main roots of taste-based discrimination against obese women.

# 6. CONCLUSIONS

In this paper we analyse the existence of wage discrimination due to obesity, its type (statistical and taste-based discrimination) and its relationship with individuals' job characteristics, making a distinction between workers´ contacts with people inside and outside the firm. The results obtained for white men in the US show that, despite not detecting a wage penalty in aggregate terms, there are some specific occupations where discriminatory behaviour can be identified. The fact that all these jobs share the trait of involving intense contact with people outside the company, but not inside, rejects employers´ and co-workers´s prejudice as the roots of discrimination against obese males, putting instead the burden on customers. This is a novel result in this literature where the consensus finding was no wage discrimination against obese men.

As regards white women, we do find that they suffer wage discrimination because of their physical appearance, regardless of their productivity. In line with the results of Bozoyan & Wolbring (2018), this penalty is again not due to statistical discrimination. In particular, our estimates indicate that prejudice against them comes indistinctly from both clients and employers, as opposed to obese men which were only penalized by customers. This implies that employers use different criteria to assess physical appearance of men and women, punishing the latter but not the former for being obese irrespective of their productivity and the more so as women get older. A potential explanation of this finding could be that men are over-represented among employers, but not among clients, and that they exert more prejudice against the opposite sex in terms of image concerns related to physical appearance.

Finally, it should be remarked that these results are not without some limitations. First, it cannot be discarded that the occupational characteristics selected here fail to capture all the defining elements of a job potentially capable of influencing the relationship between obesity and wage discrimination. For example, the lack of detailed information on clients´ turnover could be a potential caveat. Consequently, it cannot be fully ruled out that the estimated effects suffer from OVB and therefore should be interpreted as "associations" rather than "causal" effects. Yet, accounting for the individual's work environment when addressing the issue of discrimination is key. This aspect has been often disregarded in the literature, and in view of our results, it is likely to explain some of the contradictory evidence on gender differences in obesity stereotypes reported in previous studies. Likewise, the increasing impact of age on the female obesity-wage penalty emphasizes the need for future research on this topic attempting to identify the effects of discrimination on specific demographic groups and not only on the aggregate population. Moving forward in this respect would help putting the focus of public policies not only on individuals who are subject to discrimination, but also on the environments where such actions take place.

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## Appendix. Mapping of occupational codes.

Five crosswalks are used to export the data on occupational characteristics from the O*Net Online database to our NLSY97 sample of individuals. First, the ones provided by the US Census Bureau are used to convert the COC 2002 (Census Occupation Codes 2002) codes available for each individual in NLSY97 base to SOC 2000 (Standard Occupational Classification 2000). Subsequently, SOC 2000 were converted first to SOC 2010; next, the latter to SOC 2018, and finally from SOC 2018 to the specific SOC 2010 codes of O*Net Online using the crosswalk provided by this datasetr. The "merge m:1" Stata command was the one used for all these mappings, taking the code available for each individual as indicator variable.

Since the modern codes consider a larger number of occupations than the older codes, we took as the valid occupation the one corresponding to the first number in the crosswalk sequence. Lastly, in the SOC 2018 to SOC 2010 mapping of O*Net Online, there were cases of missing codes in the latter. All of them ended in ".01". After checking that several of the missing occupations were similar to those coded under ".00", we have recoded them to this last termination and mapped them again using the "merge" command.