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*Juan J. Dolad, Luigi Minale & Airam Guerra*

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**Centre for Research and Analysis of Migration**

Department of Economics, University College London
Drayton House, 30 Gordon Street, London WC1H 0AX

cream@ucl.ac.uk

www.cream-migration.org

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

Juan J. Dolado[a,b,c], Luigi Minale [a,c], Airam Guerra [a]

(a) Universidad Carlos III de Madrid; (b) CEPR; (c) IZA

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**Abstract**

This paper investigates the roots of potential labour-market discrimination underlying the negative correlation between obesity and hourly wages. Using a panel dataset of white individuals drawn from the U.S. 1997 National Longitudinal Survey of Youth (NLSY97), we test whether residual wage gaps could be attributed to prejudice (taste-based discrimination) and/or statistical discrimination. To this end, we 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). In particular, our analysis sheds light on whether discrimination originates from clients' attitudes, fellow workers or employers. Our findings are consistent with taste-based discrimination against obese females, especially as they become older, in jobs requiring frequent communication with either clients or employers. However, the evidence on this issue is weaker for males. We conjecture that these differences may originate from both an over-representation of males among employers and different image concerns against people of the same gender.

**Keywords:** Obesity; Wages; Discrimination; Job Characteristics; NLSY97; O*Net Online.

**JEL Classification**: J71, J15, J31, J24, I10

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Corresponding author: Juan J Dolado, Dept. of Economics, UC3M, c/ Madrid 126, 28903 Getafe (Madrid), Spain. Email: dolado@eco.uc3m.es. Luigi Minale: lminale@eco.uc3m.es. Airam Guerra: aiguerra@eco.uc3m.es. We are grateful to a Co-Editor and two referees for very insightful suggestions that helped improve the paper a lot, and to Lukas Delgado, Warn Lekfuangfu, Dan Rees and participants at the 2022 COSME workshop for useful comments. Financial support from the Spanish Ministry of Science and Innovation (grant 2021/00366/001-Plan Estatal and María de Maeztu grant CEX2021-001181-M) is gratefully acknowledged. The usual disclaimer applies.

## 1. INTRODUCTION

How the rise and prevalence of obesity impinges on the population welfare and economic growth has been the subject of a vast interdisciplinary literature (Philipson and Posner, 2003). In that regard, 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). Likewise, the economics literature has long recognised the growing impact of overweight/obesity on expenditures in health insurance and social security systems (Trasande and Chatterjee, 2009). Relying on all this evidence, the World Health Organization (WHO) has declared growing obesity as one of the major worldwide health problems and a global epidemic since 1997 (Rohana et al., 2020).

In parallel with these developments, research on how wages and obesity are related has gained scientific and media relevance since the mid-1990s.[1] In particular, a common empirical finding is a negative association between obesity and female wages, mainly among white women, whereas 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 to fill this gap by using very rich longitudinal information from the 1997 National Longitudinal Survey of Youth (NLSY97) that helps analyze whether the above-mentioned negative correlation could be attributed to statistical and/or taste-based workplace discrimination, once other productivity differences are considered. Classifying different types of jobs according to their specific characteristics (such as the extent of oral communication involved or the importance of dealing with customers) and identifying which of these traits turn out to be more consistent with discrimination being exerted by either co-workers, employers, customers or agents outside the company facilitate achieving these goals. To identify which part of the association between body weight and hourly wages could be attributed to workplace discrimination, we regress individual hourly wages on our preferred measure of obesity in panel data regressions including a rich set of productivity-related characteristics, such as demographic, human capital,

[1] Baum & Ford (2004) and Majumder (2013) examine this issue using data for the US (2016); Lin (2016) and Huang et al. (2015) 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.

health status and occupational controls.[3] Following the literature, we tackle the potential endogeneity of obesity (i.e. the possibility that low wages cause obesity) by instrumenting the respondent's body weight measure with that of a close biological relative – the mother and the closest sibling – while leave-one-out instruments are used to account for potentially endogenous occupational changes. Likewise, we analyse the relevance of omitted variable bias (OVB) in the case where unobserved variables cause both obesity and low wages. In all instances, we find qualitatively similar empirical results indicating that an identification strategy based on the large set of observables available at the NLSY97 does not seem to be at odds with the hypothesis that obesity lowers wages for reasons unrelated to productivity differences.

Our results show no overall discrimination effect in the case of men while a significant impact of discriminatory practices is found for women. More precisely, we show that an increase of one standard deviation in the chosen measure to capture obesity (Body Fat Percentage, or BFP in short; see Section 3.2 for its definition) is associated with a reduction of 2.1 log points in female wages. When the regressions include interaction terms of occupational characteristics with BFP, we identify significant wage penalties for women (and to a much lesser extent for men) in jobs involving intense direct contact with the public and consumers. Furthermore, the effect is also significant for women in jobs requiring frequent public speaking or where mistakes involve serious consequences for the firm. Particularly important is the finding that older obese women suffer a stronger penalty, which we argue goes against statistical discrimination while being consistent with taste-based discrimination.

**Related Literature Review**. Two early studies on the topic are Gortmaker et al. (1993) and Sargent and Blanchflower (1994). These authors regress individual wages on a lagged value of a body weight measure (in addition to other controls) to guard against reverse causality, namely, low income leading to a poorer diet and worse physical conditions (see Clark et al., 2020).[4] Both studies find a negative statistically significant relationship between obesity and wages among women but not for men, a result which is repeated in most of the subsequent literature. A noticeable caveat, however, is that the use of lagged regressors does not necessarily preclude the potential existence of

[3] Please refer to Section 4.1 for a detailed discussion on the plausibility of considering the estimated residual wages as stemming from discrimination rather than other alternative explanations.

[4] Typically the body weight measure is the Body Mass Index (BMI), defined as BMI = $\frac{Weight\ (kg)}{[Height\ (m)]^2}$

endogenous factors, leading to some OVB. To overcome this limitation, Averett and Korenman (1996) propose using the difference between the individual's body mass index (BMI) and 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. Their main finding is the lack of a statistically significant relationship between wages and obesity for either gender which could be due to the small sample sizes used in their study (about 800 couples). Similarly, Pagan and Davila (1997) address the endogeneity problem through the use of instrumental variables (such as family poverty level and health limitations, plus a self-esteem indicator) whose validity, however, is rejected by a Hausman test on the instrument exclusion restrictions.

In line with those studies, Cawley (2004) uses a similar estimation approach applied to a much larger sample drawn from the 1979 NLYS. Once more, 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.[5] As regards black and Hispanic women, despite finding a negative correlation, their estimated coefficients are smaller in absolute value than those for white women and even lack statistical significance when the regressor of interest is the BMI difference. The estimated coefficients for men of any race are either statistically insignificant or even slightly positive for whites.

In turn, Baum and Ford (2004) analyse Cawley's (2004) sample, this time by means of a panel data model including individual fixed effects (FE) estimated in first differences. Their main findings are again a negative significant impact of BMI on female wages and an insignificant one for men. Furthermore, as in the present paper, one of the main goals of these authors is to try to identify the channels behind this negative relationship among women. To this end, they include interactions of the BMI with different proxies of job characteristics, the health status of the individual, an indicator variable for employer-paid health insurance and, finally, seniority in the company.[6] Among all these controls, only job experience turns out to be significant, pointing to an adverse impact of obesity on

[5] Cawley (2004) also uses gender/race IV regressions to cater with the endogeneity of BMI. Though it cannot reject the null in a Hausman test, the paper provides ample behavioural genetic literature in support of the IV exclusion restriction.

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

female wages as women get older. As for men, estimates are smaller and are only significant in jobs involving close contact with clients.

Within the line of research looking at the channels linking fitness with wages, Bhattacharya and Bundorf (2009) only find an obesity wage 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 among males. Neumark, Bank and Van Nort (1996) and Rooth (2009) address the identification of the roots of discrimination regarding physical appearance by exploring the relationship between beauty and the probability of being hired. Their findings, common to both genders, imply that less attractive people are less likely to get jobs. 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.

Several studies have explored the different channels of weight-based discrimination (see, among others, Averett (2014) for a nice review of this literature). De Beaumont (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) follow a similar approach, this time replacing the occupations mentioned above with 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 male wages. At the same time, women happen to be penalised in those trades that require oral communication or serving. Hence, clients are pointed out as a potential source of taste discrimination. Likewise, Moro et al. (2019) fail to find empirical support for sorting of overweight people in the U.S. into jobs requiring little interaction with the public. Lastly, it is noteworthy that, while BMI has been widely used as a standard measure of obesity in the literature, several researchers and the WHO (1995) have argued that it might fail to distinguish body fat from non-fat body components since the former relates to obesity while the latter captures muscularity, skin, organs, etc. As a result of these criticisms, Wada and Tekin (2010) and Bozoyan and Wolbring (2011) have proposed body fat percentage (BFP) as an improved measure of obesity in their studies of how weight relates to wages in the U.S. and Germany, respectively. 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 with a random-effects (RE) estimation approach because time variation in variables like body fat and non-fat body mass is insufficient to justify using 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 paper relates to the strand of the literature that analyses how the origin of the obesity-wage penalty by gender relates to a wide range of job characteristics in different sectors. Yet, the empirical evidence about the different types of weight-based discrimination is somewhat disjoint across different studies. We aim to estimate the relative contribution of different types of discrimination, such as taste-based and statistical. 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 RE approach used by Bozoyan & Wolbring (2018), applied here to a large and rich sample of the U.S. population drawn from the NLSY97, which provides detailed information on a wide range of physical-fitness variables. In relation to this literature, our main methodological contribution is threefold. First, we provide a much more detailed analysis of the heterogeneity of the impact of obesity on wages by gender. Second, we use BFP rather than the criticised BMI as the variable of interest. Third, we conduct a more thorough study of the origin of workplace discrimination (statistical or taste-based) by focusing on each job's skill requirements and characteristics. Specifically, to identify sources of potential obesity discrimination due to prejudice, we consider a wider set of occupational characteristics than in previous closely related studies on this topic (e.g. Baum and Ford, 2004; DeBeaumont, 2009; and Han et al., 2009), informing about direct contact with clients, employers or other economic agents outside the company. Some of these detailed job characteristics are useful to rationalise some previously unexplained results in this literature. Furthermore, whereas most of these studies use FE estimation, we argue that RE may be a more appropriate approach when the variable of interest (BFP) does not exhibit high variability over time for a given individual.

As already anticipated, our most relevant findings can be summarised as follows. First, there is weak empirical support for wage discrimination among obese male workers. However, some prejudice is found in jobs involving external communication with people outside the firm, like customers or suppliers. Second, we document stronger taste-based wage discrimination against female employees coming mainly from their interactions with clients and employers. Moreover, this effect happens to be particularly relevant among older women in jobs involving higher responsibility and frequent oral communication. Thus, it seems likely that the existence of gender-specific expectations on how physical appearance matters for men and women could explain gender differences in stereotypes. A potential reason for these differences could be that men are overrepresented in managerial positions and discriminate more against obese workers of the opposite gender regarding image concerns. For example, according to the US Bureau of Labor Statistics (BLS), slightly above 60% of managers were men during the period under consideration.

The outline of the rest of the paper is as follows. Section 2 reviews the basic theoretical framework underlying the link between wage discrimination and obesity. Section 3 describes the database and the set of variables used in the empirical section. Section 4 discusses the empirical strategy, while Section 5 presents the main results. Finally, Section 6 concludes. An Appendix provides additional information regarding 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, namely: (i) differences in human capital and (ii) potential discrimination.

Regarding human capital, the wage gap could be due to the lower productivity of obese workers through worse health conditions or physical performance. For example, Baum and Ford (2004) test for explanations related to health limitations, less training due to greater time discount rates, and the shift to lower wages of higher health insurance paid by employers. However, their main finding is that none of these mechanisms is able to fully explain why obese workers experience persistent wage penalties.

As a result, the persistence of wage gaps among individuals who exhibit different weights but identical productivity could be interpreted as a cost for discrimination incurred by consumers/employers, which is transferred to the worker through lower wages. In such instances, as is well known, discrimination could be of two types.

**Statistical discrimination.** Statistical discrimination occurs in settings where the principal should assess the agent's productivity without observing it directly. In this context of asymmetric information, the group of 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 can observe the true productivity of the agent, obese workers' wages would converge to the same pay achieved by slender workers with the same levels of human capital. A simple way to summarise the main implications of the statistical discrimination theory is provided by 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 to their benefit.

**Taste-based discrimination.** Taste-based discrimination (or pure prejudice) is present whenever the degree of discrimination does not vanish as information on the agent's productivity 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 the higher wage $W_o(1 + d)$, where $d$ is Becker's (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 $W_o/1+d$. Otherwise, if only a few firms discriminate, Becker's well-known prediction is that they will be competed away by non-discriminating firms. Second, suppose the root of discrimination stems from co-workers in a given job. In that case, 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, non-obese 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 slender workers will have to be compensated through higher wages than those received by their fellow obese workers with identical skills. Since it is difficult to identify these roots of discrimination separately in the absence of audit or experimental studies, our empirical approach relies on lumping these two cases together and using 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 employees and their customers happen to be in close or frequent contact. In other words, consumers will base their demand for 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 exerting discrimination, such as regulators and suppliers, for whom the same reasoning applies. As mentioned above, our approach relies on interacting measures of these 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 those subject to high client turnover.[7] 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 to buy in alternative shops where 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, due to 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, our dataset's lack of information on client turnover prevents us from addressing this problem. However, the wide set of occupational codes and industry dummies used in the empirical analysis is likely to alleviate this potential concern.

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 exert 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 prior beliefs on the lower productivity of these people translate into greater potential losses for firms. The same reasoning applies to clients experiencing greater dissatisfaction when employees poorly execute services.

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

## 3. DATA AND SAMPLE SELECTION CHARACTERISTICS

### 3.1 Panel data: US NLSY97

Our sample consists of panel data 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 representative sample of young individuals residing in the US were interviewed annually between 1997 and 2011, and biannually between 2011 and 2017. Respondents are are full-time or part-time employees in the civil sector, born between 1980 and 1984, aged between 17 and 21, and 27 and 31 years old in the first (2001) and last round (2011), respectively. As already stated, we only consider white respondents of both genders to avoid other confounding sources of discrimination based on ethnicity. Furthermore, due to their alteration in body weight during pregnancy, pregnant women are excluded from the sample. We also drop individuals whose height is below 114 and above 213 cm and whose weight is outside the 31-180 kg range.[8] Finally, we omit individuals for whom there is incomplete information on all the variables considered in the study. As regards the dependent variable in all our regressions, in line with the literature we choose the individual's hourly wage, which is capped at a maximum of $ 500 per hour.

After applying 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 instances.[9]

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

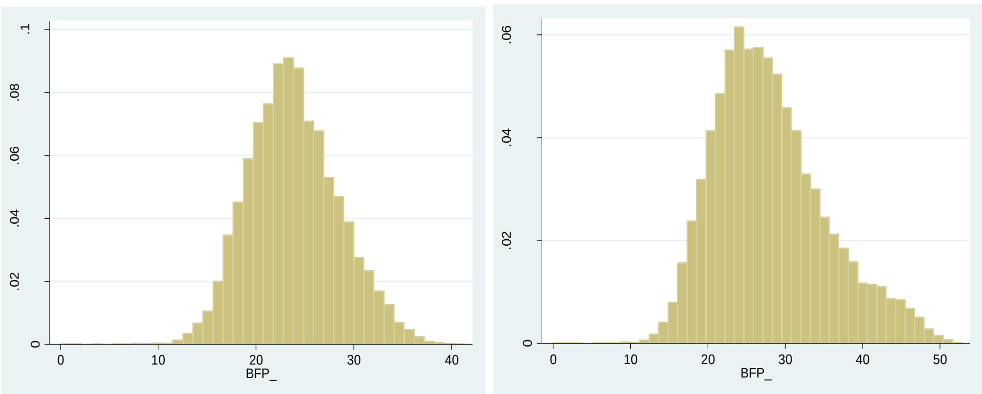
In line with the criticisms made by Burkhauser & Cawley (2008), Wada and Tekin (2010) and Bozoyan and Wolbring (2011, 2018) on the low representativeness of BMI as a proxy for an individual's physical condition, in the sequel we follow these authors' choice of the percentage of body fat (BFP) as the anthropometric explanatory variable of interest. BFP is defined as the ratio between an individual body fat (BF onwards) and

[8] Analysing self-employed workers´ labour earnings would be an interesting approach to measure customers´ discrimination, which is left for future research.
[9] To check whether sample selection is a problem, we have carried out a Kolmogorov-Smirnov (KS) test for the null of equality of the c.d.f´s of the selected and excluded samples, yielding a p-value of 0.143.

their total weight (measured in the same units).[10] Unfortunately, NLSY97 does not collect direct measures of BFP or BF, though 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 generalised 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 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 U.S. between 1988 and 1994 which reports BFP measures. The specification of the predictive equations for FFM follows the ones in Wada (2007), yielding $R^2s$ above 0.80 for each gender.[11] Histograms of BFP are depicted in Figure 1 for men (left panel) and women (right panel), whose specific features are summarised below in Table 1.

**Figure 1: Distribution of BFP by gender**

Men Women




*Note:* Authors' elaboration from NLSY97 data.

10 $BFP = \frac{Body\ Fat\ (kg)}{Body\ weight\ (kg)}$

11 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.

### 3.3 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, we consider seven different variables: (i) "Being in contact or working directly with the public" ($Cont\_Pub$), (ii) "Importance of working with clients or the public in the job" ($Imp\_Clients$), (iii) "Frequency with which workers have to speak in public" ($Speak\_Freq$), (iv) "Importance of communicating with supervisors or colleagues within the company" ($Comm\_Int$), (v) "Importance of communicating with other people outside the company" ($Comm\_Ext$), (vi) "Consequences of making a mistake at work" ($Job\_Mistake$), and (vii) "Importance of using analytical thinking at work" ($Analy\_Think$). We extracted each of these variables, defined by as an index ranging from 0 to 100 (from less to more important), 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.[12] Further details on the mapping procedure are provided in the Appendix.

### 3.4 Control variables and descriptive statistics

The NLSY97 collects a wide variety of data on respondents in terms of demographic, economic, health (including height and weight) and human capital.

Demographic controls include dummy variables for the region of residence ($Northeast$, $Northcenter$, $West$ and $East$), urban area 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 U.S. native ($Native$ equal to 1) and years of education of the father and mother ($Years\_Ed\_Fath$ and $Years\_Ed\_Moth$, respectively).[13]

As for the set of human capital and employment experience controls, we consider the following covariates: years of tenure in the same firm ($Tenure$), having moved 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

[12] 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/).

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

($Training$ equal to 1), years spent in full-time, part-time employment and in unemployment ($Years\_FT$, $Years\_PT$ and $Years\_Unem$ respectively),[14] years of completed education ($Years\_Ed$), and the percentile obtained in the ASVAB cognitive test of mathematics and verbal in 1999 (ASVAB_p_1999).

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 "poor"), $Times\_Sick$ refers to the number of times the individual has suffered an injury or illness during the last year, and $Days\_Sick\_Pay$ is defined as the number of days of paid sick leave individuals took in the last year. Note that the last two covariates allow us to control for changes in productivity associated with absenteeism (see Cawley et al. 2021)

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.

Table 1 shows the descriptive statistics for the variables considered in our empirical analysis. 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 higher educational attainment, especially in terms of college degree completion, and represent a higher share in white-collar jobs. According to WHO (1995), BFP greater than 0.25 (0.33) defines obesity 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 U.S. population 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, female workers score higher in jobs involving contact with clients and other agents external to the firm. At the same time, job mistakes made by women are thought to have more serious consequences than those made by men.

[14] 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 an unemployed worker is somone who has worked less than 1 hour a week.

**Table 1. NLSY97 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 |
| **Occupational 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 | 41.066 | 16.8 | 47.892 | 17.697 |
| Analytic_Think | 63.177 | 14.394 | 64.505 | 12.517 |
| Observations (person-year) | 9,658 | | 8,823 | |
| Individuals | 1,684 | | 1,554 | |

*Note*: For the meaning of the acronyms in column 1, see subsections 3.3 and 3.4 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 real hourly wages and BFP is explained by differences in observable productivity-related characteristics. 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 covariates ($DemC\_it$) listed above, industry dummies (14) and year-time effects ($Ind_s$ ,$Year\_t$). Next, to reduce OVB, we augment this regression with the human capital controls ($HKC\_it$), health controls ($HealthC\_it$) and occupational characteristics ($OccC\_it$).

Specifically, the two regression models under consideration at the first stage are:

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

$$lnW_{it} = Controls\ in\ (1) + \beta_k * HKC_{it} + \beta_h * HlthC_{it} + \beta_{oc} * OccuC_{it} + e_{it} \quad (2)$$

Admittedly, some of the controls in equation (2) could be arguably endogenous, e.g. job change or tenure. Accordingly, some instrumental variables will be used in the sequel to cater for these problems. Yet, as will be discussed below, the instrumented and non-instrumented estimates are fairly similar implying that endogeneity does not seem to be a big concern in evaluating the extent to which such covariates can explain the obesity wage gap given that they also affect productivity.

Once we controlled for all the above covariates, we interpret the surviving estimated effect of BFP on wages as likely attributable to discrimination. We are nonetheless aware that such residual effect might also result from the correlation between BFP and other wage determinants not considered in this study, such as preferences over occupational choices, differences in human capital quality and self-esteem, and asymmetries in household interactions[15]. However, although we cannot rule out that the inclusion of

[15] Individuals suffering obesity may have different preferences and priorities when it comes to choosing occupations. They may prioritize job characteristics that align with their personal circumstances and physical limitations by choosing, for instance, jobs that offer flexibility in work hours or locations. They may also value job security or a less physically demanding work environment to accommodate their needs. Regarding the role of household interactions, if individuals with obesity are more likely to take on caregiving responsibilities or have limited mobility, they may have fewer opportunities for full-time employment or career advancement. Further, they may have lower level of self-esteem, body image, and confidence, which may result in worse job performance and wage negotiation skills.

further controls would decrease (or increase) the coefficient of BFP, we cannot rule out either that some of those factors might result from decisions influenced by discrimination. In order to assess how relevant these concerns are, we implement Oster (2019)' s methodology to test for the potential relevance of omitted unobserved components (not captured by the observed controls) in biasing the estimates (see Section 5.1). The results from this exercise support the argument that the potential role of any remaining omitted unobserved components is minor in our setting.

### 4.2 Disentangling statistical from taste-based discrimination

In 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:

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

The insight for including these interaction terms in (3) is as follows. On the one hand, if statistical discrimination exists, 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 become negative in this case. Conversely, suppose this coefficient turns out to be positive and statistically significant. In that case, discrimination should be interpreted as nepotism in favour of obese workers and, if insignificant, as discrimination based on prejudice whenever the coefficients of the interactions of BFP with the occupational characteristics are negative.

On the other hand, those older individuals who have accumulated longer tenure are likely to have provided solid information about their real productivity (in the form of a longer resumé, recommendations or recognition within the sector). 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. Of course, we could observe that both types of discrimination (or none) play a role depending on the sign, the size, and the significance of the respective estimates. Table 2 summarises the previous interpretations of discrimination roots according to the signs of the $\beta_2$ coefficients on the interaction terms of BFP with the three controls mentioned above.

**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 sector characteristics, again in separate regressions like (2) above. As before, their estimated coefficients' sign and statistical significance 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, we consider a triple interaction specification 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 by means of 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 in (4) for simplicity, 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 $OccI$, where the coefficients $\beta_2$ and $\beta_5$ determine the sign and slope of this change. If both coefficients were statistically significant and shared the same sign ( or if only $\beta_5$ turns out to be significant), the level of $OccI$ will only modify the semi-elasticity indicator up or down. However, if they have opposite signs, there would exist a cut-off level in $OccI$ above or below which the direction of the above-mentioned effect would differ, provided that the threshold value falls in between 0 and 100 (the range 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, values above the cut offs would point to prejudice. 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 positive discrimination for values above it.

## 4.4 Estimation and identification

**Estimation procedure.** 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:[16]

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

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. We claim that including a wide host of demographic, human capital, health

[16] Following Bozoyan and Wolbring, (2011), the justification to discard FE estimation is the low time-variation of BFP in our sample. However, as shown in section 5.1, estimates obtained using FE are very similar in magnitiude, although less precise than those obtained with RE-GLS.

and occupational characteristics controls in (4) could substantially reduce OVB in the coefficient on BFP by restricting the range of potential unobservables. Yet, there would still be reasons to worry that the equation above does not yield unbiased estimates of the impact of BFP. One of them is reverse causality (see Pagan and Davila, 1997) because individuals with low income might tend to do less physical exercise and have a higher intake of cheap food rich in fat and sugar. Another possibility is that third unobserved factors (such as myopic preferences or ability) are the common cause of both obesity and labour market outcomes (see Averett, 2014). Finally, BFP might be measured with error.

**Instrumenting respondent's BMI.** To tackle the previous threats to identification, we start by implementing Oster (2019)' test to assess the potential relevance of omitted unobserved components (not captured by the observed controls) in biasing the estimates (see Section 5.1). Second, we use Joshi and Wooldridge (2009)'s RE-2SLS, instrumenting respondents' BMI with that of a biological family member - the mother and the closest sibling - following, among others, Cawley (2000 and 2004) and Brunello and D'Hombres (2007).[17] On the one hand, the BMI of a biological family member is expected to be a powerful instrument for the respondent's BMI as it takes advantage of the high heritability of obesity demonstrated in various studies.[18] Therefore, the relevance condition of our instruments is likely to be met. On the other hand, the exclusion restriction requires that the BMI of a biological family member is not correlated with the error term in the wage equation. A potential concern about the instrument's validity is that shared household environment might potentially affect both obesity and labour market outcomes. However, the available evidence suggests that the effect of shared household environment on weight is negligible; in fact, the weight of non-biological relatives is usually only loosely correlated with the respondent's weight (see Cawley and Meyerhoefer, 2012). Another potentially more serious concern is that genes affecting obesity might also affect other features correlated with the genetic component of the error term in the wage equation (see Cawley, 2015). Lacking precise genetic information, as in Kushner et al. (1990) or Norton and Han (2008), it is hard to assess how much the above

[17] Specifically, we link the mother's original sample identification category in NLSY79 to her offsprings corresponding number in NLSY97. In this fashion we are able to match a total of 5,532 person-year observations for white men and 4,654 for white women. Likewise, following Cawley (2004), an adult biological sibling's BFP is used as an alternative instrument, leading to corresponding samples of sizes 4,443 and 3,617, respectively.

[18] Studies based on twins show levels of heritability for BMI up to 70-80% (Farooqi and O'Rahilly, 2007).

argument is a valid concern in our setting. Yet, we employ two different instruments, and the fact that they provide similar estimates reassures us about their validity.

**Instrumenting "*job change*" and "*tenure*".** Another issue in estimating equation (5) above is the potential concern about some key variables in the analysis, such as *job change* and *tenure*, being "bad controls"; they are outcomes as much as wages since those individuals with higher (lower) weight may experience different pattern of job mobility. To address this problem, we use "leave-one-out" IVs to instrument those variables. Formally, the instruments for those two variables for a given individual $i$ in industry $I$ and occupation $o$ at time $t$ are defined as:

$$z_{I,o,t}^{-i} = \frac{\sum_{I,o} x_{I,o,t}\, empl_{I,o,t}}{\sum_{I,t} empl_{I,o,t}}$$

where $x$ is either the averages of $Job\_Ch$ or $Tenure$, excluding individual $i's$ and $empl$ is employment in a given occupation and industry. Intuitively, this instrument exploits the aggregate variation in job mobility patterns at the industry-occupation-year level, supposedly independent of the respondent's characteristics. These types of instruments are common in the labour literature, and the underlying assumptions justifying the exclusion restriction is, in this specific case, that $z^{-i}$ cannot affect wages directly or that it does not affect other people's wages that are related to individual $i$'s wage.

## 5. RESULTS

### 5.1 Productivity and occupational characteristics.

**Main results.** Table 3 presents the results of the first-stage regressions (1) and (2) for men and women. As shown in columns II and IV, adding the second set of controls hardly modifies the BFP point estimates obtained in the basic regression (1) (reported in columns I and III) for each gender. Regarding men, the BFP coefficient is positive but lacks statistical significance in either specification. Accordingly, discrimination against obese males does not seem to be a serious issue according to this preliminary evidence. As for women, though wage obesity gap becomes a bit smaller once the extra controls are added, the effect of BFP on wages remains clearly negative and statistically significant at 5 percent level. With the set of controls in (1), an increase of one standard deviation of the BFP (0.0672) implies a reduction of 2.1 log points (= - 0.0672x 0.316) in female wages while the wage loss slightly declines to 1.8 log points with the additional controls in (2).

In line with the arguments above, our working hypothesis is that the (residual) female obesity wage penalty could be attributed to discrimination.

**Table 3: Body Fat Percentage (BFP) and Wages**

| | **Men** | | **Women** | |
|---|---|---|---|---|
| **Dep. var: $LnW$** | **(I)** | **(II)** | **(III)** | **(IV)** |
| BFP | 0.175 | 0.121 | -0.316*** | -0.267*** |
| | (0.225) | (0.204) | (0.087) | (0.105) |
| DemC & IndD | Yes | Yes | Yes | Yes |
| HKC, HlthC & OccD | No | Yes | No | Yes |
| Nobs | 9658 | 9658 | 8823 | 8823 |
| Nind. | 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 | 0.314 | 0.223 | 0.408 |

*Note:* RE-GLS estimation. Controls are described in section 4.1. All columns include industry and year dummies. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

To analyse the potential role of omitted unobserved components (not captured by the observed controls) in biasing the estimates, we resort to Oster (2019)'s results on the relevance of this bias, which are based on coefficient movements scaled by the change in R-squared when extra controls are included in the regression (as in the extended specification (2) above). Assuming an equal selection relationship between observables and unobservables, and denoting the vector of estimated coefficients under specifications (1) and (2) by $\widehat{\boldsymbol{\beta}}_{\mathbf{1}}$ and $\widehat{\boldsymbol{\beta}}_{\mathbf{2}}$, respectively, Oster (2019) derives a consistent estimator of $\boldsymbol{\beta}$ given by the vector of adjusted estimates $\breve{\boldsymbol{\beta}} = \widehat{\boldsymbol{\beta}}_{\mathbf{2}} - \xi(\widehat{\boldsymbol{\beta}}_{\mathbf{1}} - \widehat{\boldsymbol{\beta}}_{\mathbf{2}})$ with $\xi = \frac{R^2_{max} - R^2_2}{R^2_2 - R^2_1}$. In this expression $R^2_1$ , $R^2_2$ and $R^2_{max}$ are the (overall) R-squared from the two specifications and a hypothetical regression including all the relevant observables and unobservables, which, of course, is unfeasible and has to be set a priori. Oster (2019) recommends setting it equal to $1.3R^2_2$ in practice, which implies that the contribution of unobservables to total wage variation is assumed to be 30 percent at most. For illustrative purposes, with the computed $R^2{'}s$ and the estimates of the BFP slopes for women in colums III and IV of Table 3, the adjusted estimate becomes $\breve{\beta} = -0.222$ while, according to column IV, the corresponding slope estimate in specification (2) is $\hat{\beta}_{\mathbf{2}} = -0.267$. The fact that both estimates are fairly close suggests that the potential role of any remaining OVB is not very relevant in our setting; thus, in the sequel we take (2) as our maintained specification.

While the previous results correspond to RE-GLS estimation, Table 4 provide a comparison of those estimates with the alternative ones obtained by RE-2SLS, where mothers' (panel A) and sibling's (panel B) weight (in both cases converted into BFP through the process described in Section 3.2) are used as an instrument for the individual's BFP, respectively. These are strong instruments since the Kleinbergen-Paap test yields p-values of 0.016 (mother) and 0.009 (sibling). As can be observed, at the cost of some efficiency when applying RE-GLS, the above comparison yields largely robust results about the obesity wage penalty by gender: in both instances the BFP slope estimate is close to -0.3. Hence, potential reverse causality does not seem to be a big issue here, possibly because obesity traits tend to appear much earlier than the age at which individuals enter the labour market. Hence, unless differently stated, only RE-GLS estimates will be reported in what follows.

**Table 4: Comparison of BFP estimates by RE-GLS and RE-2SLS**

| **Panel A: Mother's BFP as Instrument** | | | | |
|---|---|---|---|---|
| ***Dep. var: LnW*** | **Men** | | **Women** | |
| | **RE-GLS (I)** | **RE-2SLS (II)** | **RE-GLS (III)** | **RE-2SLS (IV)** |
| BFP | 0.106 | 0.089 | -0.278*** | -0.294* |
| | (0.236) | (0.302) | (0.116) | (0.151) |
| Nobs | 5532 | 5532 | 4654 | 4654 |

| **Panel B: Closest Sibling's BFP as Instrument** | | | | |
|---|---|---|---|---|
| ***Dep. var: LnW*** | **Men** | | **Women** | |
| | **RE-GLS (I)** | **RE-2SLS (II)** | **RE-GLS (III)** | **RE-2SLS (IV)** |
| BFP | 0.092 | 0.134 | -0.263*** | -0.305** |
| | (0.273) | (0.356) | (0.093) | (0.126) |
| Nobs | 4443 | 4443 | 3617 | 3617 |

*Note: Panel A:* RE-GLS estimation and RE-2SLS with mother's weight (transformed into BFP) as IV. *Panel B:* RE-GLS estimation and RE-2SLS with closest sibling's weight (transformed into BFP) as IV. All columns include demographic, human capital, health, occupational controls and industry and year dummies. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Next, Table 5 (columns II and IV) reports RE-2SLS estimates using sibling's BFP and the leave-one-out IVs for *Job_Ch* and *Tenure* described earlier where, again for comparison, the RE-GLS estimates are also included in (columns I and III). As can be seen, the estimates obtained with instrumented *Job_Ch* and *Tenure* are similar to those obtained with RE-GLS, implying that biases arising from the potential endogeneity of these two decision variables are also bound to be small.

**Table 5: Comparison of BFP, Job change and Tenure coefficient estimates by RE-GLS and RE-2SLS**

| ***Dep. var: LnW*** | **Men** | | **Women** | |
|---|---|---|---|---|
| | **RE-GLS (I)** | **RE-2SLS (II)** | **RE-GLS (III)** | **RE-2SLS (IV)** |
| BFP | 0.0101 | 0.126 | -0.284*** | -0.312** |
| | (0.313) | (0.397) | (0.102) | (0.131) |
| Job change | 0.008 | 0.005 | 0.029*** | 0.045*** |
| | (0.011) | (0.013) | (0.008) | (0.013) |
| Tenure | 0.029*** | 0.033** | 0.035*** | 0.052*** |
| | (0.011) | (0.013) | (0.012) | (0.014) |
| Nobs | 4443 | 4443 | 3617 | 3617 |

*Note:* RE-GLS estimation and RE-2SLS with closest sibling's weight (transformed into BFP), and leave-one-out instruments as IVs for "Job change" and "Tenure". All columns include demographic, human capital, health, occupational controls and industry and year dummies. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01

**Robustness checks.** As mentioned earlier, if BFP changes little across time (its standard deviation is one-fifth of its mean in the first row of Table 1), a FE specification may yield standard errors too large to tolerate relative to RE-GLS models. Yet, the trade-off is that their coefficients are more likely to be biased if the set of controls does not capture relevant unobservables. Table 6 reports both sets of coefficients rendering insignificant wage effects when FE is applied. However, the estimated coefficients on BFP by FE are not too different from those obtained by RE which supports the use of this last estimation procedure.

Another issue worth checking is the linear effect of BFP on wages. In Table 7, we allow for a quadratic functional form where the variable BFP squared is marginally significant for men but not women. Given this result, we keep the linear specification in the sequel since it greatly simplifies the computation of double and triple interactions.

Lastly, we follow the approach by Moro et al. (2019) to test for selection vis-à-vis non-employed individuals (about 5%) in our sample of wage earners by estimating a Heckit model for the wage equation corrected for this type of bias. Like these authors, we model a first-stage probit for participation using the closest sibling's employment status in NLSY97 as identifying variable to construct Heckman's lambdas. The idea is that job referrals by these close relatives affect the participation decision without affecting wages.

Table A.1 in the Appendix reports the results and the RE-GLS estimates, showing that the Inverse Mills ratios for men and women are not statistically significant, in line with Moro et al.'s (2019) general findings for NLSY 1982-96.

**Table 6: Comparison of coefficients on BFP estimated by RE-GLS and FE**

| ***Dep. var: LnW*** | **Men** | | **Women** | |
|---|---|---|---|---|
| | **RE-GLS** | **FE** | **RE-GLS** | **FE** |
| BFP | 0.118 | 0.092 | -0.285*** | -0.224 |
| | (0.196) | (0.432) | (0.114) | (0.465) |
| Nobs | 7973 | 7973 | 7257 | 7257 |

*Note:* RE-GLS and FE estimates. All columns include demographic, human capital, health, occupational controls and industry and year dummies. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

**Table 7: BFP and Wages: Nonlinear specifications**

| ***Dep. var: LnW*** | **Men** | **Women** |
|---|---|---|
| | **RE-GLS** | **RE-GLS** |
| BFP | 0.138 | -0.227*** |
| | (0.204) | (0.093) |
| BFP^2/100 | -0.162* | -0.125 |
| | (0.087) | (0.094) |
| Nobs | 9658 | 8823 |

*Note:* All columns include demographic, human capital, health, occupational controls and industry and year dummies. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

**BFP and occupational characteristics.** Table 8 reports the estimated coefficients on the interactions of BFP with occupational indicators of interpersonal communication with internal and external agents in separate regressions like (3). The results in column I 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 communication (at 10%). As regards women, the results in column II 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 penalisation of obese women who have to speak in public and deal with clients, but not for those communicating with outsiders, as was the case for

**Table 8: Interactions between BFP and Occupational Characteristics**

| Interaction of BFP with/ | Men (I) | Women (II) |
|---|---|---|
| Being in contact or working directly with the public | -0.0127** (0.0063) | -0.0137* (0.0071) |
| Importance of communicating with other people outside the company | -0.0200* (0.0105) | -0.0073 (0.0069) |
| Importance of communicating with supervisors or colleagues within the company | 0.00286 (0.0152) | 0.0012 (0.0112) |
| Frequency with which workers have to speak in public | 0.0111 (0.0097) | -0.0232*** (0.0068) |
| Importance of working with clients or the public on the job | -0.0143* (0.0084) | -0.0097*** (0.0036) |
| Importance of using analytical thinking at work | 0.0041 (0.0113) | -0.0054 (0.0097) |
| Consequences of making a mistake at work | 0.0028 (0.0092) | -0.0209*** (0.0068) |

*Note:* RE_GLS estimation with $lnW$ as the dependent variable. Separate regressions are run for each interaction term by gender. 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 are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

men. This result points to a specific niche of job environments where prejudice against obese women occurs, more closely related to speaking in public rather than 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 statistically significant effects extend theirs.[19] Finally, another novel 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 against than the other when working in front of the public, the penalty for making mistakes and oral communication could imply that obese women

[19] 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.

might 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 9 shows the estimated coefficients of the BFP interactions with the discrimination indicators ($DicsI$). In the case of men, none of their 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 provides 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 log points (= -(0.286+0.249x0.49)x0.0672)), which is 0.7 pp. higher than the 2.1 log points effect reported earlier (see Table 3) 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, suggesting the presence 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, providing support against statistical discrimination.

**Table 9: Interactions between 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. 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 are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

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

Tables 10a (men) and 10b (women) display the results of the last-stage regressions, which include triple interactions of BFP with $Tenure$ (i.e. the most relevant covariate in the $DiscI$ set in Table 8) 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). Given the large number of regressors, we just report the estimates that turn out to be significant at the 10 percent level and the triple interactions in all instances. As can be inspected, the estimates of the $\beta_5$ coefficients on the triple interactions are statistically significant in most cases, particularly for women. Yet, in contrast with the results in Table 8, 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 the type of discrimination.

In the case of men (see Table 10a), 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 in favour of taste-based discrimination against obese 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 male sample means (0.53 and 53.3, respectively), the estimated coefficient on the triple interaction in column I of Table 10a implies that an increase of one s.e. in BFP (0.0672) is associated to a reduction of 0.94 log points (=-(0.005x53.3x0.53)x0.00672)) in the hourly wages of obese workers in close contact with customers.

**Table 10a: Triple Interactions: BFP, Discrimination Indicators and Occupation Characteristics (Men)**

| **Dep. var: $lnW$** | **(I)** | **(II)** | **(III)** |
|---|---|---|---|
| BFP | --- | --- | --- |
| Tenure | 0.033*** | 0.029*** | 0.031*** |
| | (0.010) | (0.011) | (0.010) |
| Occupation | -0.002* | --- | --- |
| characteristic. | (0.001) | | |
| BFP * Tenure * | -0.005** | | |
| Ext_Comm | (0.002) | | |
| BFP * Tenure * | | -0.003 | |
| Cont_Pub | | (0.002) | |
| BFP* Tenure* | | | -0.002 |
| Imp_Clients | | | (0.002) |
| $N_{Obs.}$ | 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 $lnW$ as the dependent variable. The occupation characteristics are the ones appearing in the triple interactions, whose acronyms are defined 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. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01

However, in stark contrast to men, the estimates on the double interaction of female BFP and $Tenure$ in Table 10b remains negative and significant, though the size of its coefficient is smaller than in Table 9. As for the triple interaction terms, only the estimated coefficient on the interaction of BFP with $Tenure$ and $Cont\_Pub$ is insignificant. In contrast, the estimates on the three remaining interactions exhibit highly significant coefficients. For instance, using the estimates in column IV and evaluating $Tenure$ and $Imp\_Cons$ at their female sample means (0.487 and 72.6, respectively) implies that an increase of one s.e. in BFP (0.0672) is associated with a 2.7 log points reduction (=-(0.180+0.182x0.487+0.0036x0.487x72.6)x0.0672)) in hourly wages where the contribution of the triple interaction is 0.9 log points, that is, about one third of the total effect. Overall, we interpret this evidence as supporting that customers and other internal agents are the main roots of taste-based discrimination against obese women.

**Table 10b: Triple Interactions: BFP, Discrimination Indicators and Occupation Characteristics (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) |
| Tenure | 0.345*** | 0.036*** | 0.030*** | 0.032*** |
| | (0.008) | (0.009) | (0.009) | (0.010) |
| Occupation ch. | -0.019** | -0.012** | -0.016** | -0.014* |
| | (0.008) | (0.005) | (0.008) | (0.008) |
| BFP * Tenure | -0.188** | -0.177** | -0.207*** | -0.182** |
| | (0.091) | (0.085) | (0.077) | (0.090) |
| BFP*Occ | --- | -0.0132* | --- | --- |
| | | (0.007) | | |
| BFP* Tenure* Job_Mistake | -0.0038** (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 | 0.406 | 0.413 | 0.420 | 0.418 |
| $R^2$ between | 0.410 | 0.416 | 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 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. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Finally, to guard against potential endogeneity concerns regarding the previous RE-GLS results, we proceed to estimate again the regression in Table 10b for women (for men, the results in Table 10a were far less conclusive) using this time RE-2SLS with siblings' BFP and the leave-one-out occupation-industry instruments as IVs for individual's BFP and $Tenure$, respectively. Table 11 shows the corresponding estimates. Results are similar to those shown in Table 10b, with the same interaction terms displaying significant coefficients, therefore yielding further support to the finding that customers and other internal agents are the main roots of taste-based discrimination against obese women.

**Table 11: Triple Interactions (RE-2SLS): BFP, Discrimination Indicators and Occupation Characteristics (Women)**

| **Dep. var: $lnW$** | **(I)** | **(II)** | **(III)** | **(IV)** |
|---|---|---|---|---|
| BFP | -0.234** | -0.223** | -0.199** | -0.180** |
| | (0.118) | (0.127) | (0.109) | (0.089) |
| BFP * Tenure | -0.212* | -0.217** | -0.238** | -0.212** |
| | (0.127) | (0.112) | (0.116) | (0.112) |
| BFP*Occ | -0.0082 | -0.0182* | -0.0087 | -0.0065 |
| | (0.0989) | (0.0102) | (0.0074) | (0.0068) |
| BFP* Tenure* | -0.0049** | | | |
| Job_Mistake | (0.0018) | | | |
| BFP * Tenure* | | -0.0066** | | |
| Speak_Freq | | (0.0034) | | |
| BFP * Tenure* | | | -0.0018 | |
| Cont_Public | | | (0.0027) | |
| BFP * Tenure* | | | | -0.0045** |
| Imp_Clients | | | | (0.0023) |
| $N_{Obs.}$ | 3617 | 3617 | 3617 | 3617 |
| $N_{Ind.}$ | 700 | 700 | 700 | 700 |
| $R^2$ within | 0.343 | 0.335 | 0.327 | 0.346 |
| $R^2$ overall | 0.336 | 0.339 | 0.322 | 0.335 |
| $R^2$ between | 0.328 | 0.328 | 0.316 | 0.328 |

*Note:* RE-2SLS estimation with closest sibling's BFP as instrument for respondent's BFP and leave-one-out occupational-industry-year instruments as IV for "Tenure". $lnW$ is the dependent variable. The definition of the acronyms for each reported interaction term of BFP with tenure 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. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

## 6. CONCLUSIONS

In this paper, we analyse the potential existence of wage discrimination due to obesity, its type (statistical and taste-based discrimination) and its relationship with individuals' job characteristics, distinguishing 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' prejudice as the roots of discrimination against obese males, putting the burden on customers instead. This result is novel in this literature, where the consensus finding was the lack of wage discrimination against obese men.

Regarding white women, we find evidence 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 who were only penalised by customers. This implies that employers use different criteria to assess the physical appearance of men and women, punishing the latter but not the former for being obese irrespective of their productivity and 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, as stated throughout the paper, it should be remarked that these results are not without some limitations. First, one cannot discard that the occupational characteristics selected here fail to capture all the defining elements of a job capable of influencing the relationship between obesity and wage discrimination. For example, the lack of detailed information on client 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 seems key. This aspect has often been disregarded in the literature. Our results likely explain some of the contradictory evidence on gender differences in obesity stereotypes reported in previous studies. Likewise, the increasing association of age with the female obesity-wage penalty emphasises the need for future research on this topic, attempting to identify how discrimination operates for specific demographic groups and not only on the aggregate population. Moving forward in this respect would help focus public policies not only on individuals who are likely to be subject to discrimination but also on the environments where their actions occur.

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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 dataset. The "merge m:1" Stata command was 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 the one corresponding to the first number in the crosswalk sequence as the valid occupation. 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 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.

### Heckit model

**Table A.1: Comparison of BFP coefficient estimates by RE-GLS and Heckit**

| ***Dep. var: LnW*** | **Men** | | **Women** | |
|---|---|---|---|---|
| | **RE-GLS** | **Heckit** | **RE-GLS** | **Heckit** |
| BFP | 0.118 | 0.131 | -0.276*** | -0.326** |
| | (0.306) | (0.364) | (0.098) | (0.129) |
| Mills ratio | --- | 0.005 | --- | -0.008*** |
| | | (0.013) | | (0.014) |
| Nobs | 4443 | 4443 | 3617 | 3617 |

*Note:* RE-GLS and Heckit estimation with closest sibling's employment status as identifying variable for the Mills ratio. All columns include demographic, human capital, health, occupational controls and industry and year dummies. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.