The double burden for being women and obese: Evidence from Chilean labor market and potential explanations

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Abstract: This paper analyzes the labor market dimension of a worldwide social concern: the growing level of obesity. Using detailed individual information of Chilean workers, we find a strong evidence of a wage-penalty for women across the whole distribution of body size, whereas men seem to enjoy a wage-premium for being overweight. We test several hypotheses for explaining this finding. Our results suggest that the gender wage-gap between obese and non-obese workers is not related to neither observed productivity differences nor risk aversion or health limitations. For women, the wage penalty is mostly explained by occupational crowding and the "beauty premium" in high-skilled occupations. Finally, this study outlines some possible avenues that future research should address.

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1. Introduction

Obese individuals suffer a double burden in modern societies. In addition to facing the negative consequences on their health—such as cardiovascular diseases, stroke, diabetes, musculoskeletal disorders, among others (Pi-Sunyer, 2002)—, they must also deal with a weight-based stigma in labor markets. For instance, the empirical evidence suggests that workers who are obese are less likely to get hired (Morris, 2007; Rooth, 2009; Lindeboom et al., 2010), have lower probability to be promoted (Pagan and Davila, 1997; Roehling et al., 2013), and face lower wages (Cawley, 2004).

Despite the abundant empirical evidence of the weight-bias in labor market outcomes, what is really worrisome (from a gender equality point of view) is that the degree of discrimination against obese women is disproportionately greater than against obese men. This result is corroborated for many studies that find a negative effect for women in labor market outcomes, but weakly for men (Register and Williams, 1990; Averett and Korenman, 1996; Pagan and Davila, 1997; Bozoyan and Wolbring, 2018); and studies showing that the wage-penalty exists just for women, but not for men (Cawley, 2003, 2004; Baum and Ford, 2004; Conley and Glauber, 2006; Johansson et al., 2009; Han et al., 2009; Sabia and Rees, 2012). There is even evidence that obese women earn less than healthy-weight coworkers, but men receive a 'premium' for being heavier (Morris, 2006; Asgeirsdottir, 2011).

The fact that women might suffer a weight-penalty have aroused the interest of different feminist movements, particularly in academy (see for example Fikkan and Rothblum, 2012a,b; Chrisler, 2012; Roehling, 2012). A notorious result of this discussion is that current studies not only attempt to establish the causal effect of weight on labor market outcomes, but also try to understand the gendered nature of this bias (Cawley, 2003; Caliendo and Lee, 2013; Katsaiti and Shamduddin, 2016). An explanation for the gender differences in the relationship between obesity and wage is the theory of productivity. Accordingly, weight affects women more than men because they are more susceptible to physical limitations and absenteeism reducing their productivity (Cawley, 2003; Sabia and Rees, 2012; Greve, 2016). Another plausible explanation is mere discrimination against obese people due to employers', employees' or customer's preference or prejudice (Hamermesh and Biddle, 1994; Cawley,2003; DeBeaumont, 2009; Greve, 2016; Bozoyan and Wolbring, 2018).

Some scholars also argue that weight-stigma against women seems to be higher in contemporary western societies where larger body size is considered as an unattractive characteristic, as opposed to less developed countries or a society in transition where it can be a signal of wealth and health (Fallon, 1990; Stearns, 2002). For example, the empirical evidence for US (Averett and Korenman, 1996; Baum and Ford, 2004; Cawley, 2004; Johar and Katayama, 2012; Sabia and Rees, 2012), Canada (Chu and Ohinmaa, 2016; Larose et al., 2016) and UK (Sargent and Blanchflower, 1994), consistently show the existence of a greater wage-penalty for women than men. However, the literature for China (Shimokawa, 2008) and Sweden (Dackehag et al., 2015) find that the wage-penalty is more significant among men than women. For Brazil (Thomas and Strauss, 1997) and Guinea (Glick and Sahn, 1998) the evidence suggests that weight is positively correlated with wage for men, whereas Schultz (2003) show that this correlation is positive for both men and women in Cote d'Ivoire and Ghana. Thus, the effect of weight on earnings is likely to depend on cultural norms of a country, the degree of development and the degree of discrimination in labor markets.

Under this context, our research tries to empirically assess the potential bias towards women due to weight in the Chilean labor market. The questions we try to answer are the following: Is there evidence of a weight-penalty for being obese in the Chilean labor market? Is the pattern different for men and women? If this is so, what could be the potential explanations for such a gap?

Besides being the first study aimed at establishing a potential relationship between obesity and wages in Chile, our analysis has merit for several reasons. First, it focus in a country where the literature has shown an important gap in labor market outcomes between men and women (Bravo et al., 2009). For example, women's labor force participation is low compared to other Latin American countries (Contreras and Plaza, 2010; Puga and Soto, 2018). In terms of earnings, the gender-gap ranges between 11% and 30%, depending on the sample and method used (Gill, 1992; Fuentes et al., 2005; Perticará and Bueno, 2009; Montenegro, 2001). Second, obesity rates has alarming increased in the last years despite the constant efforts made by the Chilean government (OECD, 2019). The last report of the Food and Agriculture Organization (FAO) states that 34.4% of the population over 15 years old has high rates of obesity, placing Chile in the second position in the ranking that considers OECD countries. Furthermore, the percentage of obese women in the labor market has slightly increased from 18% in 2004 to 22% in 2015 achieving higher rates than men (see Figure 1).

(Insert Figure 1, about here)

Third, as in western societies, Chilean women tend to associate slimness with the ideal body size. For example, Robinovich et al. (2018) based on a qualitative study show that Chilean women consider being thin as an embodied form of capital in the marriage and labor markets. Another qualitative study carried out by Sprovera et al. (2017) suggests a high degree of stigmatization of the fat body by young Chileans.

Our main result indicate that heavier women, on average, earn less per hour than thinner coworker, whereas heavier men have a wage-premium, although this premium only occurs for slightly obese men. The negative wage-penalty is relatively high compare to the international results. For example, women earn approximately 15% less than men, whereas obese women earn 10% less than a healthy-weight women. We show that a substantially part of the wage-gap between obese and non-obese women cannot be explained by productivity, health limitations, impatience or other observable endowments. Our results support the hypothesis that the weight-gap for women can be partially explained by occupational crowding and "the beauty premium" in high skilled occupations, whereas for men the premium occurs in low-skilled occupations.

2. Data

2.1 EPS Survey

This work uses 4 waves (2004, 2006, 2009 and 2015) of The Survey of Social Protection (EPS) (Subsecretaría de Previsión Social, 2019). This survey was first applied in 2002 but the sample selected was only statistically representative of the people affiliated to the Chilean pension system. Because of this, that year was not considered in our analysis. Later, in 2004, the sample was expanded to include both affiliated and not affiliated people to the Chilean pension system. Despite the Ministry also applied this survey in 2012, this wave presented some statistical problems and it is not recommended to be used for performing statistical analyses (Subsecretaría de Previsión Social, 2019).

The EPS gathers detailed individual information about education, health, social security and labor history of respondents. The main objective is to provide valuable information to the design of public policies with a particular emphasis to the study of the Chilean pension system. EPS is a survey with several advantages over common data sets in Chile. First, individuals report their labor history starting from 1980, including non-employment spells, which allows us to compute the actual labor experience instead of the commonly measure of potential experience. Second, and the most important feature for our study, it includes measures of weight and height of the respondents along with several measures of family background.

We applied three main filters to the dataset. Similarly to Caliendo and Gehrsitz (2016), and since we are interested in the wage-penalty in labor market, we exclude military personnel, pensioners and respondents who are currently attending school or college. We also limit our regressions to individuals between the ages of 20 and 65. We also exclude pregnant women and self-employed workers. Our final sample corresponds to 11,269 individuals.

2.2 Wage, weight measures and controls

Our dependent variable is the (natural log of) hourly wage rate earned by the respondent in the last month at his/her primary job. This variable is adjusted to 2004 Chilean pesos using the annual variation of consumer price index. Table 1 shows that the average hourly wage is \$1,249 and \$1,130 Chilean pesos (CLP) for men and women, respectively. Using the average currency rate, these averages are equivalent to \$1.49 and \$1.35 USD being below the average hourly wage in the US.

(Insert Table 1, about here)

Each wave of the EPS asks respondents to report their weight and height. Using these two variables we compute two measures of body size: the Body Mass Index defined as the kilograms divided by the squared height in meters (BMI = kg/m^2); and clinical definitions of weight status following the international classification, which includes underweight (BMI < 18.5); healthy weight ($18.5 \leq$ BMI ≤ 24.9); overweight ($25 \leq$ BMI ≤ 29.9), and obese (BMI > 30). The average BMI in our sample is 26.66 for men and 26.59 for women (see Table 1). Furthermore, 35% and 41% of the male and female sample, respectively, can be considered as having a healthy weight. However, the proportion of obese workers is higher for the female sample (20% vs 17%). The number of respondents who are underweight is relatively very small (1% for both men and women), which, as we will observe, could affect the precision of the estimates for this group. All regressions include a set of variables to control for productivity and demographic characteristics as listed in Table 1. We also include father's and mother's education to control for family background.

3. Is there evidence of weight-penalty in Chile?

3.1 Men vs women

We start our analysis by asking whether there exists suggestive evidence of a weight-penalty in Chile. If there exists, then we ask if there is a different pattern between men and women.

Table 2 shows some preliminary unconditional and conditional correlations between the logarithm of (real) hourly wage rate and BMI using OLS. Models 1-3 pool men and women, whereas model 4 and 5 specify separate regressions for men and women, respectively. To take into account the fact that individuals are not independent, we report standard errors clustered at the individual level. Model 1 shows that the unconditional correlation between BMI and logarithm of hourly wage is negative for the whole sample: one-unit increase in BMI is predicted to decrease hourly by approximately 0.4% ($p < 0.028$).[1] Column 2 shows that— holding constant productivity, socio-demographic, family background, sectoral, regional and year-specific factors—the negative correlation does not decrease that much, yielding a weight-penalty of about 0.38% ($p < 0.011$). Model 3 tests whether the weight-penalty varies by gender by including a Female∗BMI interaction. Although, on average, it seems that there exists a weight-penalty regardless of gender (model 2), model 3 shows that a one-increase in BMI is predicted to increase men's hourly wage in about 0.47% ($p < 0.035$) and decrease women' in about 1% ($p < 0.000$), providing evidence against the hypothesis that the weight-penalty does not vary by gender. The results from model 4 and 5 confirm the fact that women might suffer from weight-penalty, whereas heavier men might have a weight-premium.

(Insert Table 2, about here)

[1] Since the dependent variable is in logarithm, we use $\hat{\theta} = \left(\exp(\widehat{\beta}) - 1\right) \cdot 100$ when commenting the results. The standard error of $\hat{\theta}$ is computed using Delta Method considering the clustered standard errors from the original OLS.

3.2 Is the wage penalty/premium sensitive to the weight measure?

Are the results sensitive to the definition of body size? Table 3 shows the conditional relationship between the logarithm of hourly wage and different measures of body weight for women and men. The weight measures are: BMI (reported just for comparison), weight in kilograms (controlling for height), logarithm of BMI and dummy variables for clinical weight classification being healthy (normal: $18.5 \leq BMI \leq 24.9$) weight the omitted category.

(Insert Table 3, about here)

For the female sample, a one-kilogram increase in weight is correlated with a decrease of 0.37% ($p < 0.000$) of hourly wage, whereas 1% increase in BMI is predicted to reduce wages by 0.27%. However, this result seems to be mainly driven by obese women as presented in column 4: obese women earn on average a 10% less than healthy ones ($p < 0.000$), however we do not find statistically significant differences between underweight, overweight and normal (healthy) weight. The weight-premium for men seems to be driven mainly by overweight individuals, which earn, on average, a 4% more than those with healthy weight ($p < 0.036$).

This gender differential can also be explained by the use of the BMI as a measure of fatness (Burkhauser and Cawley, 2008; Fikkan and Rothblum, 2012b). It has been argued that BMI is not a good measure for obesity due to its inability to discriminate how much muscle versus fat individuals have (Burkhauser and Cawley, 2008). Furthermore, it does not reflect fat content and distribution (Yang et al., 2016). Thus, the "overweight" category—based on BMI—can include men with higher muscle mass (men with above-average lean mass that can be incorrectly classified as overweight), which is a more physically attractive characteristic (Burkhauser and Cawley, 2008; Cawley, 2015). If this is the case, then the finding of overweight men experiencing weight premium could be because this group includes men who meet this standard of male physical attractiveness (Roehling, 2012).

Based on the previous argument, we further analyze the robustness of our results by considering the relative position of each individual on the weight-distribution. Thus, we consider that a woman(man) is obese if her(his) BMI was equal to or above the τth percentile of the standardize woman(men)-BMI distribution. This should mitigate the unique classification of obesity based on BMI ($BMI > 30$) which does not take into account the potential gender differences on the body fat distribution and the percentage of body fat. Figure 2 shows the results for different τth percentile thresholds. The story for women is invariant to the threshold used. The weight-penalty increases as more stringent definition of obesity is considered ranging from 6% for the middle of the distribution to 13%. For men we observe a similar result as in model 8 in Table 3: men in the middle of the weight distribution earn on average more, however, as the obesity classification is based on higher percentiles, the premium is reduced.

(Insert Figure 2, about here)

To shed more light in the non-linearity of BMI, we also compute OLS regressions including the quadratic term of BMI for men and women. Figure 3 shows the partial change of one-unit increase of BMI on log of real hourly wage at different levels of BMI. Similar to Judge and Cable (2011) we found an inverted U pattern for men (panel B) such that there exists a positive and statistically significant correlation between weight and wage up to the point of BMI = 28 (Overweight), then it is not clear that an additional increase in BMI implies a wage- premium. For women, it is always negative, but statistically different from zero starting at BMI = 19 (normal weight). Thus, women experience wage penalties at the whole distribution of BMI. These results are close to those reported by Kline and Tobias (2008) and Puhl et al. (2008).

(Insert Figure 3, about here)

Are our results similar to the international literature? To answer this question, Figure 4 plots the estimates from seven studies using the same dependent variable and using the BMI or the obese category as independent variables in an OLS context. The dashed vertical lines correspond to our estimates from Table 3. A quick look at the figure reveals that for women, and regardless of whether we consider BMI or obesity category, our estimates are in the lower tail of the distribution. That is, the penalty for being obese in Chile is comparatively greater than in other countries. For men, the weight-premium stand out for being relatively high.

(Insert Figure 4, about here)

3.3 Is there evidence that the relationship between body weight and wage is causal?

It is important to emphasize that we cannot be certain that the previous estimates for body weight are causation. The wage-gap for being obese between men and women can be due to differences in unobserved factors that determine individual performance in the labor market, or it can be the case that obese are obese because they earn less (Cawley, 2004). Furthermore, our BMI variable is based on self-reported measures of weight and height, which can bias the results due to error measurement.[2]

In this Section, we try to give some insights about the potential effect of body weight on the logarithm of hourly wage by: (1) controlling for unobserved time-invariant characteristics, (2) using and instrumental variable approach, (3) and by analyzing the impact of weight gain in future earning using matching estimators.

3.3.1 Controlling for unobserved time-invariant individual characteristics

The panel dimension of the dataset allow us to control for unobserved time-invariant individual characteristics that determine body weight and simultaneously affect wages. For example, individuals with high motivation, self-esteem, self-control, and high ability are less likely to be obese and hence earn more wage (Baum and Ford, 2004). If this is the case, then our previous estimates are downward biased, and the true weight-penalty should be more negative. To partially out these confounding effects, we use fixed-effect (FE) and random-effect (RE) models.

Columns 1 and 2 of Table 4 show the results for women using BMI and Obese category (BMI > 30) as weight measures. The FE estimates suggest that there is not sufficient evidence of a weight-penalty, whereas the RE estimates are closed to those reported for women in Table 3 (column 1). A potential explanation for the absence of significance of FE estimates is the lack of within variation for weight measures among women. Our dataset reveals that each year 91% of women remained non-obese in the next period; whereas 80% of women that were obese remained

[2] Another potential bias can be the self-selection of women into labor market (Cawley, 2004). We perform a Heckman's procedure using the number of children under 5 years old (Fuentes et al., 2005; Contreras and Plaza, 2010; Ramírez and Ruben, 2015) and the number of children between 5 and 14 years old as instruments for the propensity of women to work. The results indicate that there is little evidence of selection bias. Furthermore, the point estimates are very close to those reported in Table 3. See the supplemental online appendix.

obese. The results for men (columns 6 and 7 in Table 4) remain mostly the same as those reported in Table 3: despite of controlling for time-invariant unobserved factors, BMI has a positive (and higher) correlation with wages but being obese show no association with wages.

(Insert Table 4, about here)

3.3.2 An instrumental variable approach

Although the FE model allows controlling for unobserved heterogeneity at the individual level, there may still be endogeneity problems because body weight may be correlated with other unobserved factors that vary both individually and over time (Cawley, 2004). To deal with this issue we estimate both instrumental variable fixed effect (IV-FE) and instrumental variable random effect (IV-RE) models. Similar to Morris (2006, 2007), our instruments are the commune-level body mass index and commune-level prevalence of obesity for each gender.[3] Table 4 shows that the instruments are sufficiently strong for all specifications, but only marginally for the IV-FE model in the men sub-sample.

The point estimates for women (columns 3 and 4 in Table 4) are more negative when both BMI and being obese are instrumentalized, revealing a downward bias of the weight-penalty. Considering the IV-FE results, a one-increase in BMI is predicted to decrease women's wage in about 9%, holding constant productivity variables and unobserved time-invariant factors, whereas obese women earn, on average, 61% less. The high magnitude of the point estimate for obese women and the results for the IV-RE model cast doubt on the exogeneity of the instrument.

Considering our estimates as a whole, our results are consistent with the hypothesis that OLS estimates could be underestimated due either to a problem of omitted variables that increase wages and reduce body weight or due to a measurement error problem.

[3] For other studies that used area-based measures as instruments see for example Currie and Cole (1993); Card (1993); Grabowski and Hirth (2003), to mention a few.

3.3.3 The impact of weight in future wage

Another important issue is the impact of weight in future earnings. For example, do those who became obese during the 2004-2015 earn significantly less in 2015 than those who stayed in a healthy weight?

To fix some ideas, let the variable $d_{i,t-2004}$ be a binary treatment indicator, where $d_{i,t-2004}$=1 indicates whether individual i became obese between year $t \in (2006,2009,2015)$ in relation to 2004 and 0 otherwise. Thus, $d_{i,2015-2004} = 1$ denotes all those individuals that started either being obese or non-obese in 2004 and ended up being obese in 2015, and $d_{i,2015-2004} = 0$ denotes all those individuals that started being obese or non-obese in 2004 and ended up being non-obese in 2015. Let also y_{1it} be the hourly wage if the individual becomes obese and y_{0it} the hourly wage if the individual maintains a healthy weight in time t. One quantity of interest is the average treatment effect (ATE):

$$\tau_{ate} = \mathbb{E}(y_{1t} - y_{0t}),$$

that is, the expected difference in hourly wages in year t for becoming obese in year t respect to 2004. Another quantity of interest is the average treatment among those that became obese in year t respect to 2004 (treated):

$$\tau_{atet} = \mathbb{E}(y_{1t} - y_{0t} | d_{t-2004} = 1),$$

The problem is that we only observe y_{0t} or y_{1t}, not both, for the same individual. To compute the counterfactual we use matching estimators, which use an average of the hourly wage of the nearest individuals to impute the missing potential outcome of similar subjects that receive the other treatment level. Similar to Morris (2007), in this article we use the nearest-neighborhood matching (NNM) and the propensity-score matching (PSM). To avoid, in some degree, potential problems of endogeneity, statistical clones are found based on covariates in 2014, that is, before the treatment. Figure 5 displays the one-to-one matching estimates for women. The first row shows the ATE estimates by NNM and PSM, whereas the second row presents the ATET estimates.[4]

[4] The variables for treatment probabilities in the PSM were chosen based on the best-fitting logit model using the BIC criterion and including a series of polynomials of order 2. The overlap assumption is presented in Figure A.1 of the supplemental online appendix. There is no suggestive evidence that the overlap assumption is violated.

(Insert Figure 5, about here)

The ATE estimates are consistent between both matching techniques. Eyeballing the results, we observe that the weight-penalty are close to the OLS results. For example, the results for 2006 indicates that women that became obese in 2006, respect to 2004, earned on average 14%-16% less than those women who did not. The ATET results are estimated with more noise (probably due to the small sample that become obese), but the results for 2015 shows that women that became obese in 2015, respect to 2004, earned on average 11%-12% in 2015. Overall, the magnitude of ATET estimates become increasingly negative in subsequent years. The results for men (Figure 6) remain the same: ATE and ATET are not significant.

(Insert Figure 6, about here)

4. Explaining differences between men and women

Our results suggest that obese women are paid substantially less per hour than their slimmer counterpart, whereas men seem to have a weight-premium until they reach an unhealthy weight (obese). In the following sections, we try to give some insights about what mechanisms could explain these results.

4.1 How much can we explain of the wage-gap between obese and non-obese workers?

To answer this question, similar to Katsaiti and Shamsuddin (2016) and Caliendo and Lee (2013), we estimate the Oaxaca (1973) and Blinder (1973) (OB) decomposition.

Consider that there exists two groups of individuals: Obese (O) and Non-obese (NO) workers. Then, the difference of the average hourly wage between obese and non-obese workers can be expressed as follows:

$$\ln(w_{mean}^{NO}) - \ln(w_{mean}^{O}) = \underbrace{\left[\sum_{k=1}^{K}\left(X_{k,mean}^{NO} - X_{k,mean}^{O}\right)\beta_k^{NO}\right]} + \underbrace{\left[(\beta_0^{NO} - \beta_0^{O}) + \sum_{k=1}^{K}(\beta_k^{NO} - \beta_k^{O})X_{k,mean}^{O}\right]}$$

Explained part Unexplained part

The explained part represents the amount by which the obesity differences in hourly wage would shrink if, other things equal, obese individuals had the same mean levels of measured attributes as the non-obese individuals.The unexplained part is the obesity disparity in hourly wages that would remain even if obese individuals had the mean levels of measured characteristics as non-obese workers. However, the unexplained part is a “black box”: it might represent discrimination or any other difference in unobserved trait such as motivation or any other omitted variable (Altonji and Blank, 1999). Given these limitations, we refrain from giving it discrimination meaning.

Columns 1 and 2 of Table 5 show the OB decomposition for women and men, respectively, considering as obese those workers whose BMI > 30 and using as observed attributes the same controls used in Table 2.[5]

(Insert Table 5, about here)

For women, the main result is that the unexplained part is statistically different from zero and economically significant representing the 67% ($p < 0.000$) of the total difference between obese and non-obese women, which is slightly higher to Katsaiti and Shamsuddin (2016)’s results (60%). The explained part is also significant and represents the remaining 33% of the total average difference ($p < 0.000$). The results for men are consistent with our previous results: there are no significant differences between obese and non-obese men once we control for productivity, family background, year, sectoral and regional dummy variables.

4.2 Potential explanations of the wage-gap

In what follows, and similar in spirit to Cawley (2003), Caliendo and Lee (2013) and Baum and Ford (2004), we test some theories that might help to explain such gender differences in the wage-gap between obese and non-obese workers.

[5] Following Jann (2008)’s suggestion, we use the coe cients from a pooled model over both groups as the reference coefficients.

4.2.1 Presenteeism and absenteeism

It is argued that obesity leads to physical/mental limitations or comorbidities decreasing the productivity and performance at work ("presenteeism") (Neovius et al., 2009; Hammond and Levine, 2010), and/or increasing the number of days of absence from work due to sickness ("absenteeism") (Cawley, 2003; Neovius et al., 2009) creating an additional cost to employers. Thus, the employer might offer lower wages to obese individuals because they are perceived to be less productive (Baum and Ford, 2004; Atella et al., 2008).

To test whether heavier workers earn less than non-obese peers because they are less productive, we re-estimate the OB decomposition including presenteeism and absenteeism measures as additional variables. Our proxies for presenteeism are three dummy variables indicating whether the worker: (1) needs help or have trouble performing strenuous exercise, (2) needs help or have trouble to walk long distances, and (3) needs help or have trouble to climb stairs. Our variable for absenteeism is a dummy that equals one if the worker required sick leave during the year.

Since the absenteeism variable is only available for 2009 and 2015, columns 3-6 of Table 5 shows the OB decomposition with (With P&A) and without the new variables as controls (Without P&A) to check whether the results are driven by the smaller sample size. For women, the explained part is statistically different from zero, representing the 43% of the total gap (column 3). However, the unexplained part remains both statistically and economically significant. Indeed, including the controls reduces the unexplained part in just 2%. For men, there is not evidence of a wage-gap, even after controlling for P&A (column 6). In summary, adding health limitation indicators helps to increase the explained part, but it does not reduce significantly the size or statistical significance of the unexplained part for women.

4.2.2 Risk aversion

Another potential explanation for the wage-gap for obese women is the time preference hypothesis. Accordingly, individuals with higher rate of time preference are less patient and therefore are not willing to forego current utility in exchange for long-run benefits, resulting in unhealthier behaviors (Komlos et al., 2004; Cawley and Ruhm, 2011) and less investment in human capital (Baum and Ford, 2004). Since a measure time preference (or impatience) is difficult to obtain from national representative survey, some researchers use the degree of risk aversion as a proxy (Baum and Ford, 2004). Its use is based on different studies that have found a relationship between risk aversion and obesity (Anderson and Mellor, 2008; Ikeda et al., 2010; Lawyer et al., 2015; Koritzky et al., 2012). Furthermore, risk aversion and impatience have been also related to cognitive ability, which in turn affects wages (Dohmen et al., 2010).

Thus, if women suffer from wage-penalty because they have higher levels of risk-taking tendencies, then it would be the case that including a measure of risk aversion should substantially reduce the unexplained part from the OB decomposition. To do so, we construct a similar measure as in Deb et al. (2011) based on hypothetical gambling scenarios. Based on the choices, our variable Risk averse takes the values 1 ("least risk averse") and 4 ("most risk averse").[6]

Columns 7-10 of Table 5 show the results. Again, since the risk-preference questions were asked in waves 2004 and 2009 only, we re-run the OB decomposition with and without the risk averse (RA) variable. The story is similar to the previous one: controlling for risk aversion does not reduce the unexplained part for women, in fact, it increases from 48% to 49%, whereas for men the difference between non-obese and obese is not significant.

4.2.3 Occupational crowding

Another explanation for the wage-gap between obese and non-obese workers is the occupational crowding hypothesis (Bergmann, 1974). This hypothesis states that wage differentials occurs because obese individuals are forced to work in (or sort themselves into) jobs with low obesity penalties, crowding the supply of labor force and reducing wages in such "obese" occupations (Sorensen, 1990; Hamermesh and Biddle, 1994; Pagan and Davila, 1997). Thus, an individual earn less if he/she is employed in a job held predominantly by obese rather than one held predominantly by non-obese.

To give some insights about this hypothesis, we estimate the following wage regression for men and women separately:

$$\ln w_{its} = \alpha + x_{it}'\gamma + \beta_1 O_{it} + \beta_2 CW_{ts} + \beta_3 O_{it} \times CW_{ts} + \epsilon_{its} \qquad (1)$$

where O_{it} is a dummy variable indicating whether the individual i is obese in year t; CW_{ts} is our measure of crowding representing the proportion of obese women/men in occupation s in time t; and x_{it} is the same set of controls used in Table 2. Following Hamermesh and Biddle (1994), we test the following hypotheses using model (1). If $\beta_1 = \beta_3 = 0$ and $\beta_2 < 0$, then confining obese

6 The supplemental online appendix further explains how this variable is created.

workers in certain occupations pushes down the wages for all workers in those occupations, regardless of the underlying reason of crowding (Occupational crowding hypothesis). If being obese matters only on those occupations where worker's look and health matter, then we should observe that $\beta_3 < 0$ and $\beta_1 = \beta_2 = 0$. This result agrees with the productivity explanation of wage-gap. If there exists some degree of (customer or employment) discrimination, then we should find that $\beta_1 < 0$ and $\beta_2 = \beta_3 = 0$.

The results from columns 2 and 4 in Table 6 show that, for both women and men, crowding of obese individuals reduces wages, but the correlation is higher for women. A one percentage increase of obese individuals in a given occupation reduces wages by 4% $(p < 0.002)$ for women and by 1% $(p < 0.001)$ for men. Column 6 of the Table 6 shows that the results for men are consistent with the crowding hypothesis. The results for women (column 3) show mixed but interesting results. First, it seems to exist differences in wages due to discrimination $\left(\hat{\beta}_1 < 0\right)$, and for non-obese women working in occupations dominated by obese women $\left(\hat{\beta}_2 < 0\right)$. Despite the fact that obese women experience a penalty for being in obese occupations $\left(\hat{\beta}_2 + \hat{\beta}_3 < 0\right)$, this penalty is lower compared to non-obese women $\left(\hat{\beta}_3 > 0\right)$. In particular, being obese has a penalty for those occupations where crowding is below to 30%; above this percentage obese women has a premium (but is not statistically significant).[7]

(Insert Table 6, about here)

How much the unexplained part is reduced when controlling for crowding? The results for women in Table 5 (column 11) show that, when controlling for occupational crowding, the unexplained part is substantially reduced compared to our benchmark model in column 1: by controlling for the amount of obese women in each occupation the unexplained part falls from 67% to 44%. The results for men remain the same, except that the explained part is not longer significant.

Thus, the results from Table 6 and 5 suggest that although crowding explains the wage-gap quite a bit, women may also suffer some kind of discrimination in occupations where the

[7] This figure is found by taking the partial derivative of Equation 1 respect to O_{it} and equating it to zero.

proportion of obese women is relatively low. Thus, it could be the case that obese women earn less in occupations where "the beauty premium" is higher (Hamermesh and Biddle, 1994).

To further test this idea, Table 7 and 8 show the OB decomposition for women and men, respectively, by occupational groups: whether a person works in a high/low skilled white- or blue-collar job. [8] Column 1 of Table 7 shows that the wage-gap between obese and non-obese women and the unexplained part—which represents the 97% of the total wage-gap—are statistically significant for women employed in high-skilled white-collar occupations, whereas there is not evidence of a statistically significant wage-gap for the rest of the occupations. Note also that obese male workers (Table 8) earn more than non-obese in almost all the occupations, but the difference is significant for blue-collar workers.

5. Conclusion

This study analyzes the potential wage-gap for being obese in Chile; a country considered as a developing country and where the degree of social stigma against obese women is relatively high according to qualitative studies.

When analyzing the impact of excess weight on hourly wage for men and women, we observe that there exists evidence of a wage-penalty for women across the whole distribution of body size, whereas men seem to enjoy a wage-premium for being heavier, but only until they reach a very unhealthy weight. Specifically, our results indicate that on average a woman earns approximately 15% less than a similar qualified man with similar size body, whereas an obese woman earns on average 10% less than a similar qualified but more healthy-weight woman. These findings reveal two important results. On the one hand, they give evidence of the double penalty for being a woman and obese in the Chilean labor market, and on the other hand, it provides additional evidence that the bias against excess weight remains gender-based.

Considering the gender perspective of the Chilean labor market allows us to provide a broader picture where our results are placed. As mentioned, unlike men, women in Chile are penalized for being obese, a result that might be simply reflecting a "machista" society as noticed by Contreras and Plaza (2010). These authors emphasize Chilean men consider domestic tasks and childcare as

[8] For the categorization of each individual into each type of occupation, and similar to Caliendo and Gehrsitz (2016), we use International Standard Classification of Occupations (ISCO-88) definitions.

female activities while working outside the home is identified as male duties. This traditional view of gender roles derived from "machista" cultural values might also explain why —despite the increase of women labor participation in Chile— they are concentrated in activities usually associated with female roles such as retail service jobs and office work (Carrillo et al., 2018). This process, already recognized by England (2010) as stressed by Puga and Soto (2018), entails a devaluation of job performed by women, therefore, while women intend to increase their participation in male occupations, men are not moving willingly to occupation that have been usually performed by women (England, 2010). Interestingly, our findings suggest a differentiated obese-penalty mechanism across occupations, which is consistent with the horizontal and vertical segmentation that characterizes the increase of women labor participation in Chile (Puga and Soto, 2018).

Although the causality can be analyze further in a future study, the findings for males are consistent with those reporting that overweight men earn significantly more than normal weight in US (Sabia and Rees, 2012; Majumder, 2013), Finland (Johansson et al., 2009), and studies showing that BMI increases earning among men in US (Pagan and Davila, 1997), England (Morris, 2006), Brazil (Thomas and Strauss, 1997) and Guinea (Glick and Sahn, 1998). Our wage-penalty of about 10% for obese female is higher than those found by Morris (2006) in England (1%), Härkönen et al. (2011) in Finland (5%), and Baum and Ford (2004) in US (0.7%-6.3%); close to that found by Register and Williams (1990) and Cawley (2003) for US (12%); but lower than the 20% found for both US and Germany (Cawley et al., 2005), the 18% found by in US (Conley and Glauber, 2006), and the 15% found for central Europe (Lundborg et al., 2006). A potential explanation for why the wage penalty in Chile is lower than those reported for developed countries is that Chilean employers are not required to provide health insurance to their employees.

Then, using the traditional OB decomposition we try to understand whether the obesity penalty can be explained by observe endowment differences. The results show that a substantial gap between obese and non-obese women cannot be explained by observable characteristics, whereas for men the gap is not statistically significant. We further show that the unexplained part is not statistically and economically reduced when including controls for absenteeism/presenteeism or risk aversion. Unlike Cawley (2003), these findings cast further doubt on the health and impatience channel when explaining the gender differences in the correlation between obesity and wage. For both female and male sample, occupational crowding reduces wages, however for women, as in

Han et al. (2009); DeBeaumont (2009) and Caliendo and Gehrsitz (2016), we find that the wage penalty is larger in occupations requiring interpersonal skills with more social interactions. Although the OB is susceptible to several limitations, these results hint a potential discrimination against women due to the "beauty premium", in line with the male view-based process by which Chilean woman construct their ideal bodies—besides being a socioeconomically differentiated process—stressing the character of symbolic object of the female body (Robinovich et al., 2018). Also, this finding corroborates the results for US (Cawley, 2003; Han et al., 2009; Johar and Katayama, 2012) and Germany (Katsaiti and Shamsuddin, 2016; Bozoyan and Wolbring, 2018). It should be borne in mind, however, that this finding is also consistent with a self-sorting of obese women in occupations where body size is not highly penalized (Pagan and Davila, 1997).

In light on our main results coupled with the limited empirical evidence on this topic in Chile, it is crucial that future research provides further analyses regarding to the proposed mechanisms by which obesity dampens wage rate for Chilean women. A special emphasis should be placed on the horizontal occupational segmentation that might be amplifying the wage penalty for obese woman. Importantly, future empirical research should also intent to isolate the causal effect of obesity from self selection of women across occupations. Also, future studies might shed light on the possible positive reward that slimness produces in the Chilean labor market complementing findings of qualitative analyses, which represents the other side of the coin of this social stigma.

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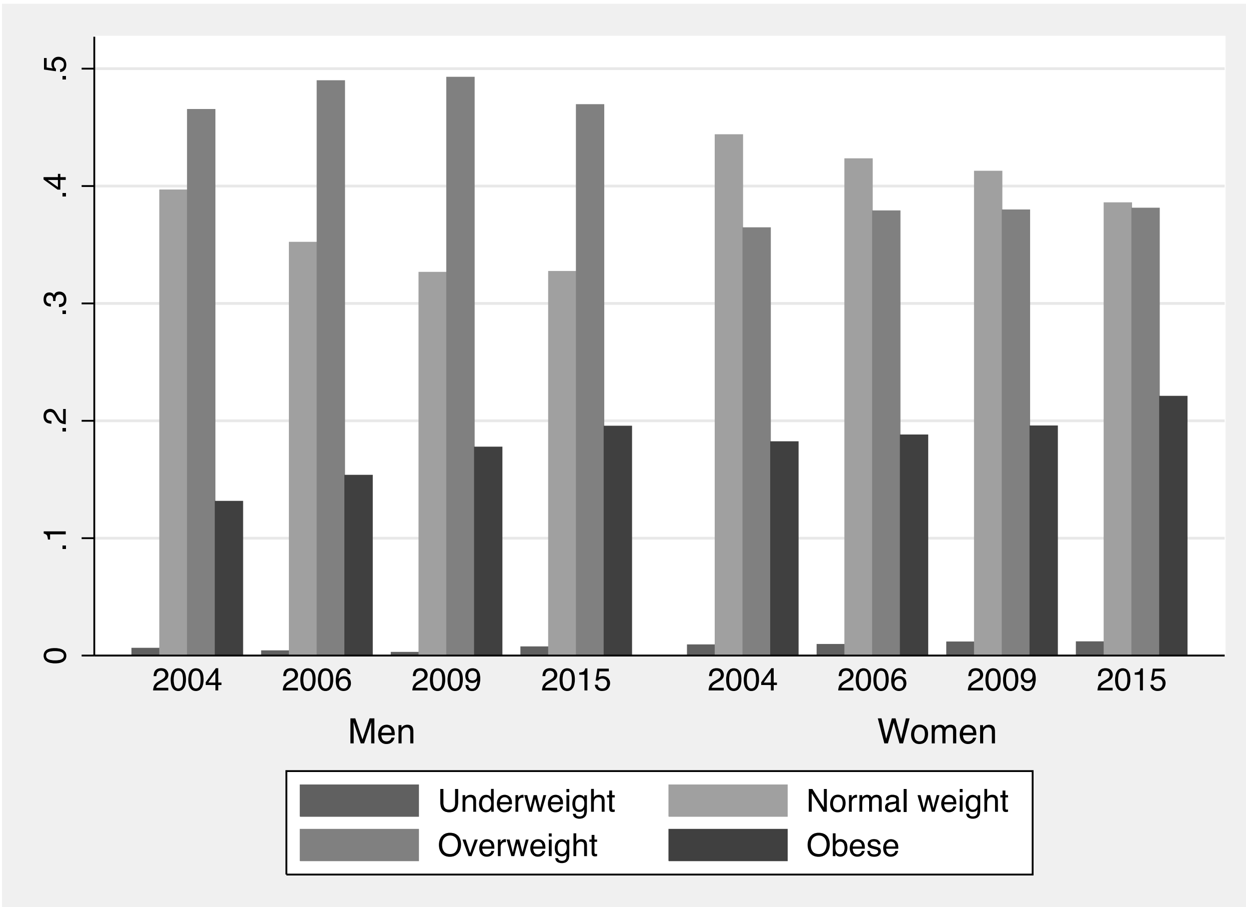
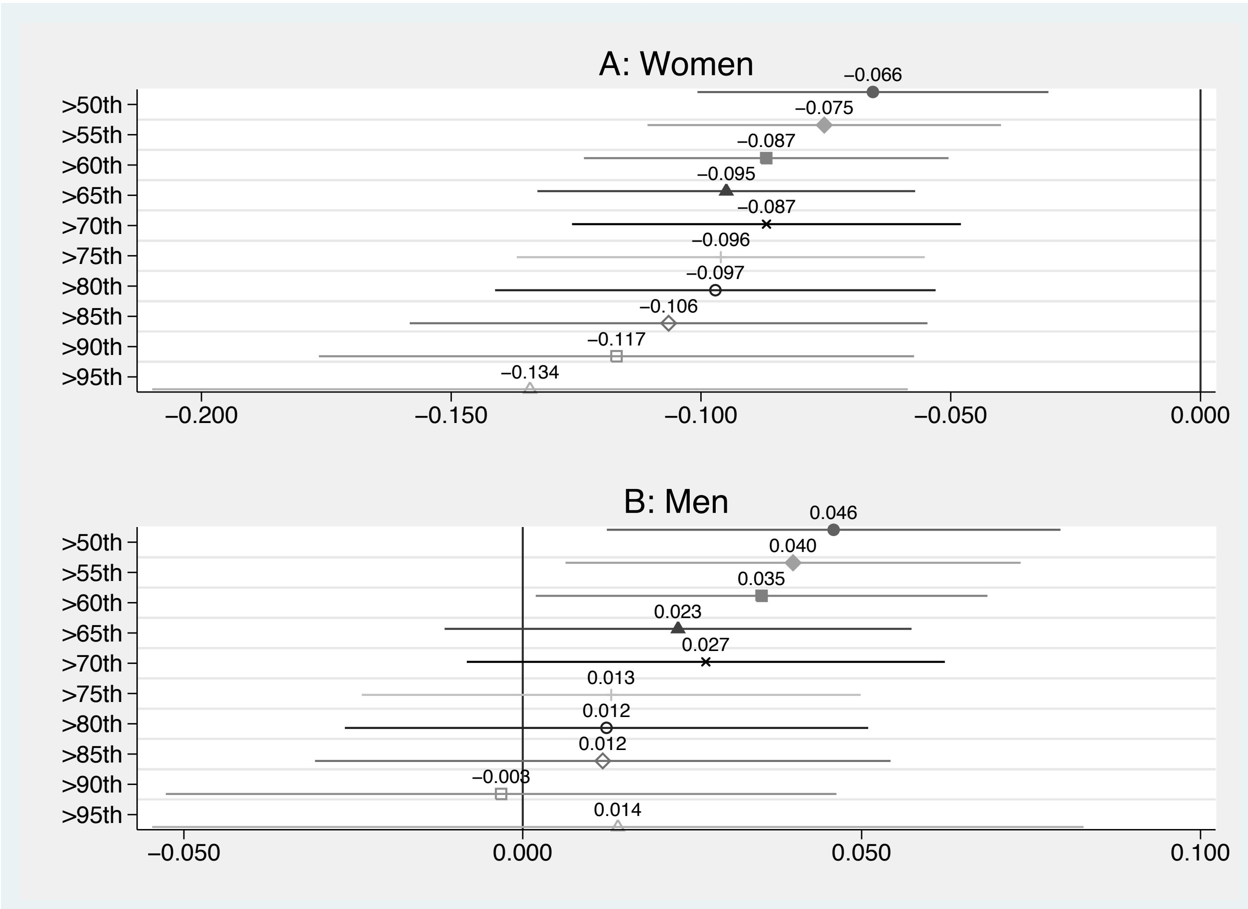
Figures

Figure 1: Distribution of weight status



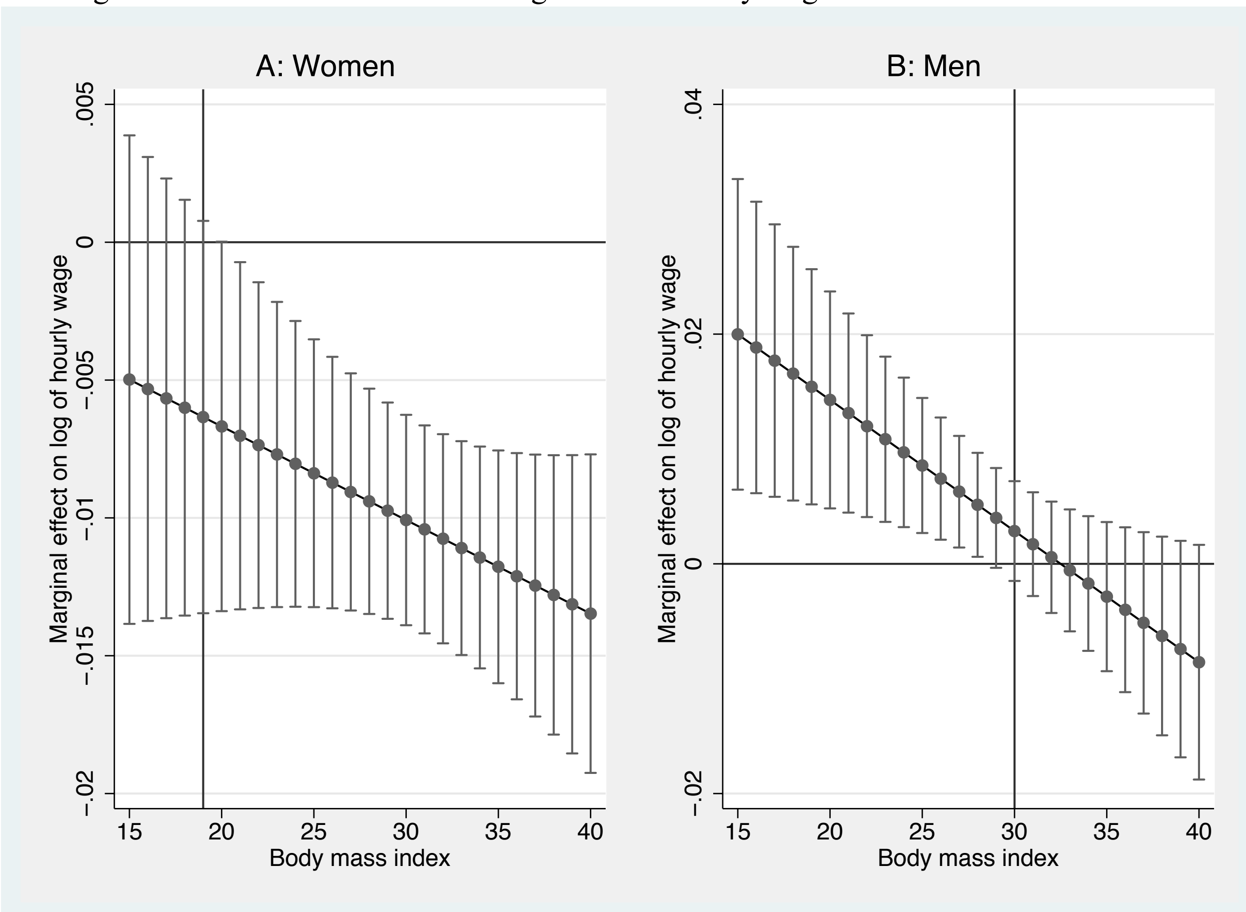
Notes: Own source based on the EPS survey. The weight categories are based on BMI: underweight (BMI < 18.5); healthy weight (18.5 ≤ BMI ≤ 24.9); overweight (25 ≤ BMI ≤ 29.9), and obese (BMI > 30).

Figure 2: Log of hourly wage and obesity based on the relative position on weight distribution (95% CI)



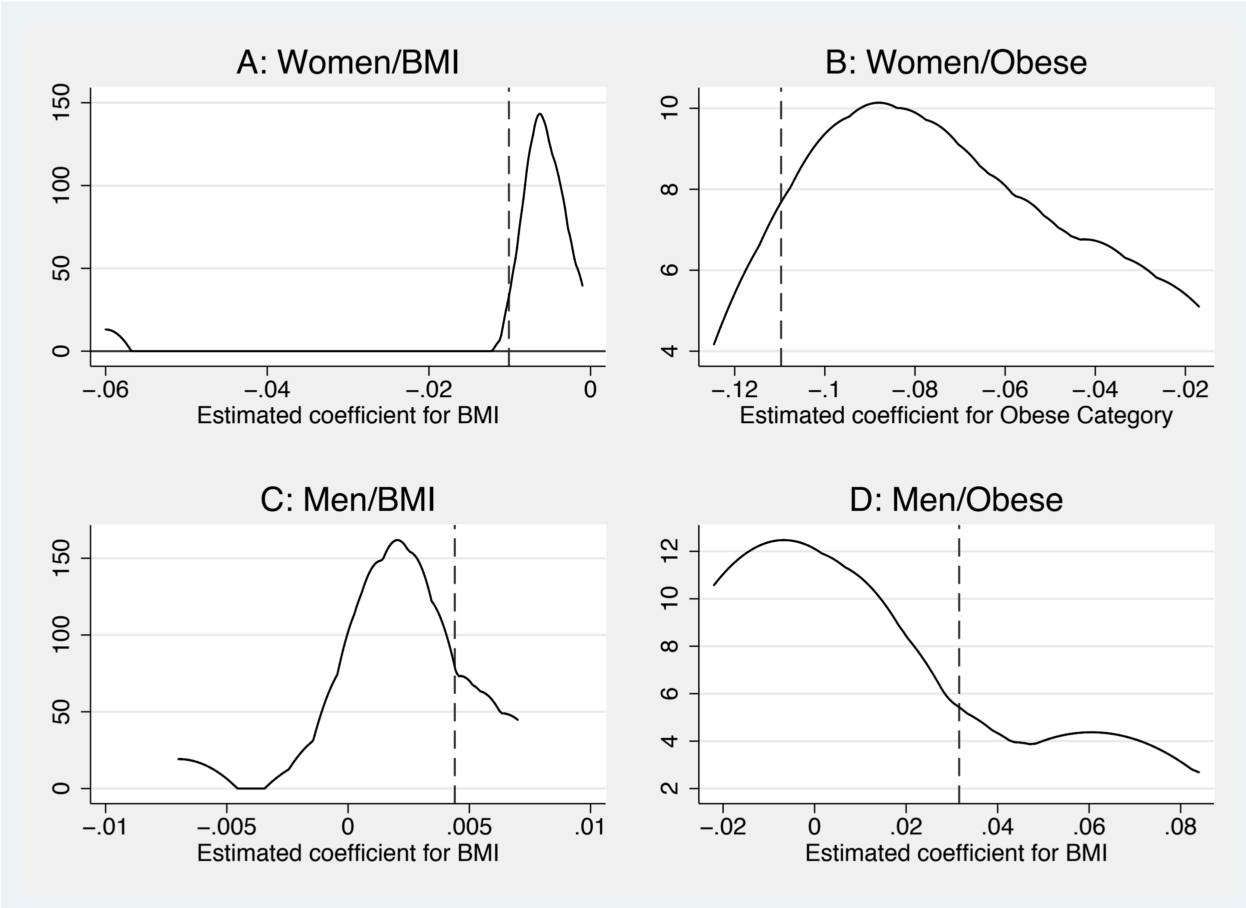
Notes: Each point estimate corresponds to the coefficient of being obese on a regression between the logarithm of real hourly wage and the same controls used in Table 2. Standard errors were clustered at the individual level. A woman (man) is considered obese if her(his) BMI was equal to or above the τth percentile of the standardize women(men)-BMI distribution. The x-axis shows the estimate for $\tau \in (0.5, 0.95)$.

Figure 3: Partial effect of BMI on logarithm of hourly wage for men and women: 95% CI.



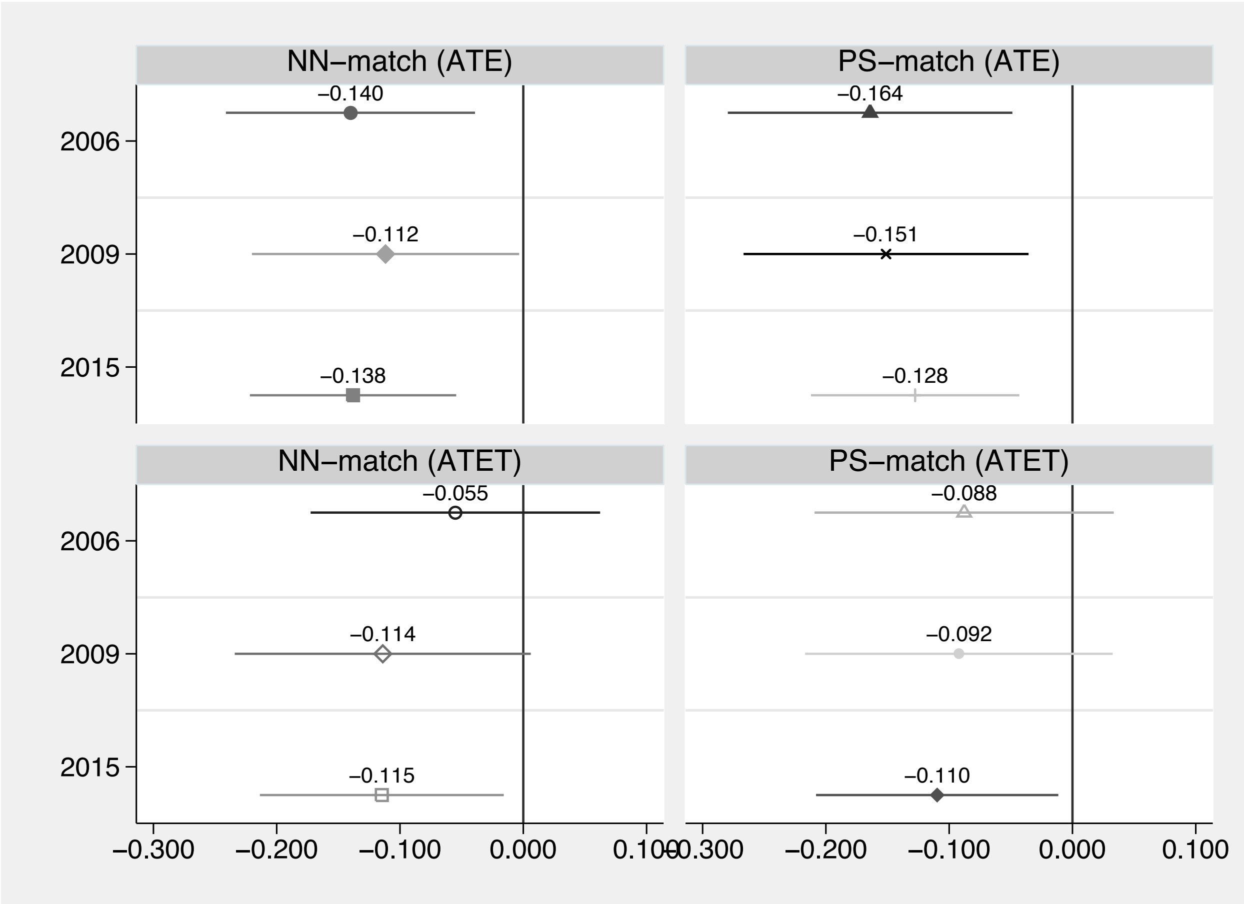
Notes: Each point estimate corresponds to the partial effect of BMI on a regression between the logarithm of real hourly wage, BMI, BMI squared and the same controls used in Table 2. Confidence intervals at 95% with clustered standard errors.

Figure 4: Distribution of BMI and obese estimates from articles using OLS



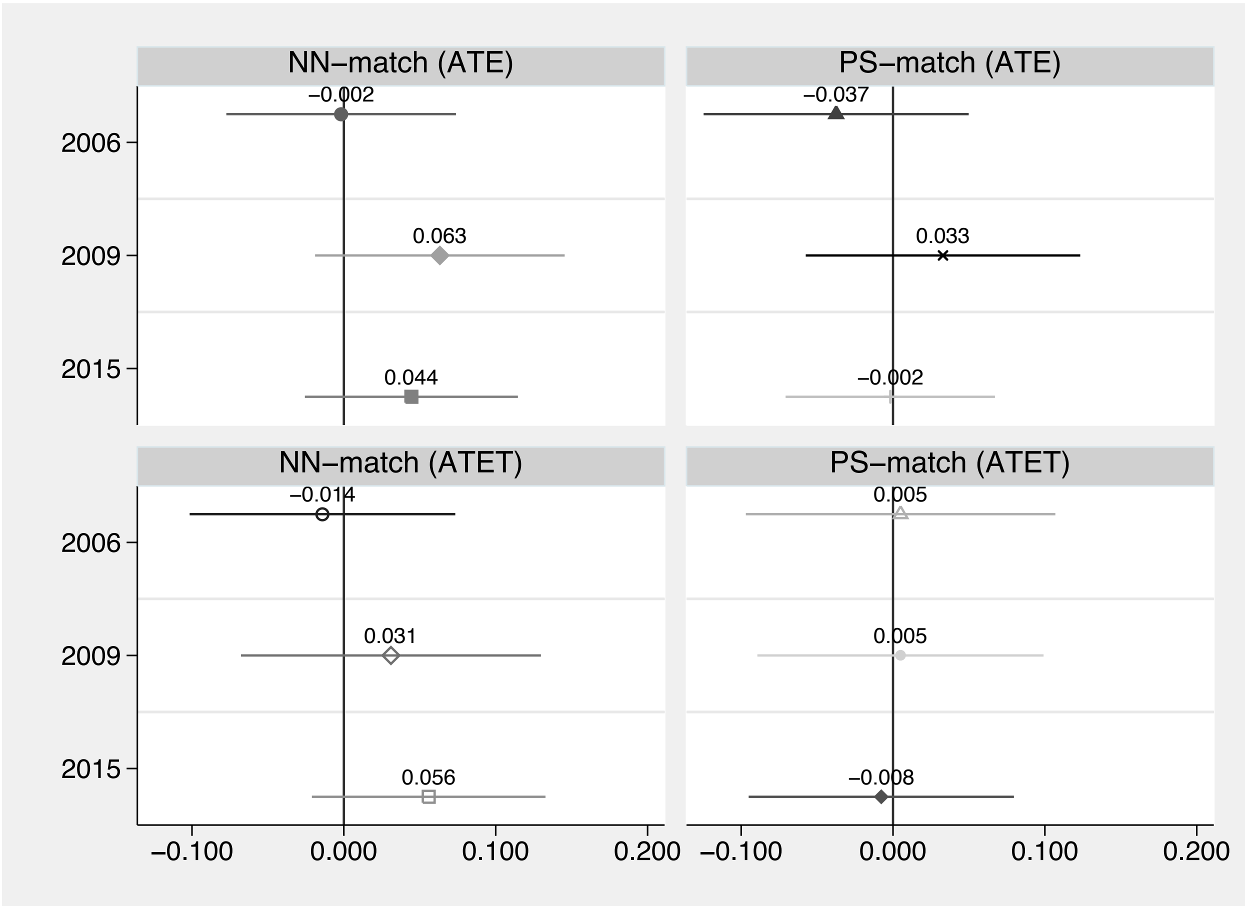
Notes: The graphs show the kernels of BMI and obese estimates from OLS equations where the dependent variable is the logarithm of hourly wage. The total number of estimated coefficients collected are: 18 for panel A, 14 for panel B, 16 for panel C and 14 for panel D. These estimates come from 7 research articles. The dashed vertical lines correspond to the estimates from Table 3.

Figure 5: NNM and PSM estimates for women (95% CI)



Notes: The NNM defines the "statistical clone" by computing the Mahalanobis distance between pair of observations with regard covariates in 2014 (age, experience, schooling, married, indigenous and mother's and father's years of schooling). The NNM estimates use the large sample correction for continuous variables. The PSM estimates defines the "statistical clone" by computing the propensity score. The 95% confidence intervals are computed using robust standard errors.

Figure 6: NNM and PSM estimates for men (95% CI)



Notes: The NNM defines the "statistical clone" by computing the Mahalanobis distance between pair of observations with regard covariates in 2014 (age, experience, schooling, married, indigenous and mother's and father's years of schooling). The NNM estimates use the large sample correction for continuous variables. The PSM estimates defines the "statistical clone" by computing the propensity score. The 95% confidence intervals are computed using robust standard errors.

Tables

Table 1: Summary Statistics

	Men					Women				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Weight Measures										
- BMI (k/m^2)	26.66	3.80	16.41	62.48	6131	26.59	4.76	15.43	80.86	5138
-Weight (in kilograms)	77.46	12.38	42	187	6131	66.65	12.28	36.00	170.00	5138
-Height (in centimeters)	170.38	6.67	140	198	6131	158.38	6.14	126.00	182.00	5138
-Underweight ($BMI < 18.5$)	0.01	0.08	0.00	1.00	6131	0.01	0.10	0.00	1.00	5138
-Normal/healthy weight ($18.5 \leq BMI \leq 24.9$)	0.35	0.48	0.00	1.00	6131	0.41	0.49	0.00	1.00	5138
-Overweight ($25 \leq BMI \leq 29.9$)	0.48	0.50	0.00	1.00	6131	0.38	0.48	0.00	1.00	5138
-Obese ($BMI > 30$)	0.17	0.37	0.00	1.00	6131	0.20	0.40	0.00	1.00	5138
Mincer's Variables										
- ln hourly wage	7.13	0.65	3.93	13.51	6131	7.03	0.67	2.18	10.55	5138
-Schooling (in years)	11.94	4.21	0.00	30.00	6131	12.95	4.30	0.00	30.00	5138
-Experience (in years)	17.32	10.43	0.00	40.52	6131	12.77	9.63	0.00	39.69	5138
-Age (in years)	40.15	12.22	20.00	65.00	6131	38.62	11.70	20.00	65.00	5138
-Married (=1)	0.64	0.48	0.00	1.00	6131	0.42	0.49	0.00	1.00	5138
-Indigenous (=1)	0.07	0.26	0.00	1.00	6131	0.08	0.26	0.00	1.00	5138
Years dummy										
-2004	0.23	0.42	0.00	1.00	6131	0.19	0.39	0.00	1.00	5138
-2006	0.23	0.42	0.00	1.00	6131	0.20	0.40	0.00	1.00	5138
-2009	0.17	0.38	0.00	1.00	6131	0.18	0.39	0.00	1.00	5138
-2015	0.37	0.48	0.00	1.00	6131	0.43	0.49	0.00	1.00	5138
Mother's education										
-No education	0.00	0.06	0.00	1.00	6131	0.01	0.10	0.00	1.00	5138
-Primary education	0.40	0.49	0.00	1.00	6131	0.45	0.50	0.00	1.00	5138
-Secondary education	0.05	0.21	0.00	1.00	6131	0.06	0.23	0.00	1.00	5138
-High education	0.05	0.22	0.00	1.00	6131	0.05	0.22	0.00	1.00	5138
-Missing	0.50	0.50	0.00	1.00	6131	0.43	0.50	0.00	1.00	5138
Father's education										
-No education	0.00	0.06	0.00	1.00	6131	0.01	0.10	0.00	1.00	5138
-Primary education	0.38	0.48	0.00	1.00	6131	0.40	0.49	0.00	1.00	5138
-Secondary education	0.04	0.20	0.00	1.00	6131	0.04	0.19	0.00	1.00	5138
-High education	0.06	0.24	0.00	1.00	6131	0.06	0.23	0.00	1.00	5138
-Missing	0.52	0.50	0.00	1.00	6131	0.49	0.50	0.00	1.00	5138

Source: EPS, own calculations based on the sample used for the estimations.

Table 2: Unconditional and conditional correlations between log of real hourly wage & BMI

	Men and Women			Men	Women
	(1)	(2)	(3)	(4)	(5)
BMI (k/m^2)	-0.0041**	-0.0038**	0.0047**	0.0046**	-0.0100***
	(0.0019)	(0.0015)	(0.0022)	(0.0023)	(0.0019)
Female		-0.1562***	0.2424***		
		(0.0155)	(0.0785)		
Female x BMI			-0.0150***		
			(0.0029)		
Productivity Variables					
Schooling (years of completed education)		0.0666***	0.0661***	0.0626***	0.0672***
		(0.0021)	(0.0021)	(0.0031)	(0.0029)
Experience (years of actual experience)		0.0127***	0.0127***	0.0038	0.0167***
		(0.0025)	(0.0025)	(0.0038)	(0.0035)
Experience^2		-0.0003***	-0.0003***	-0.0002*	-0.0003***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age		-0.0073	-0.0069	0.0063	-0.0123*
		(0.0047)	(0.0047)	(0.0065)	(0.0071)
Age^2		0.0001**	0.0001**	0.0000	0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Demographic variables					
Married (=1 if married)		0.0749***	0.0722***	0.0814***	0.0639***
		(0.0134)	(0.0133)	(0.0184)	(0.0195)
Indigenous (=1 if belongs to an indigenous group)		-0.0548**	-0.0517**	-0.0652**	-0.0391
		(0.0241)	(0.0241)	(0.0302)	(0.0387)
Mother's Education: No education as reference					
Primary		0.2208***	0.2159**	0.1286	0.1955*
		(0.0846)	(0.0845)	(0.1184)	(0.1109)
Secondary		0.1547*	0.1509*	0.0405	0.145
		(0.0899)	(0.0897)	(0.1273)	(0.1173)
High		0.2532***	0.2472***	0.1211	0.2542**
		(0.0927)	(0.0926)	(0.1287)	(0.1236)
Missing		0.1923**	0.1882**	0.0696	0.1935*
		(0.0845)	(0.0844)	(0.1182)	(0.1116)
Father's Education: No education as reference					
Primary		-0.083	-0.0805	0.0998	-0.1569
		(0.1091)	(0.1099)	(0.1861)	(0.1315)
Secondary		-0.1016	-0.0968	0.0917	-0.163
		(0.1144)	(0.1152)	(0.1924)	(0.1394)
High		0.0728	0.0736	0.2436	0.0185
		(0.1157)	(0.1163)	(0.194)	(0.1413)
Missing		-0.0342	-0.0341	0.1403	-0.1072
		(0.1095)	(0.1103)	(0.1867)	(0.1324)
Constant	7.1905***	5.9472***	5.7257***	5.4638***	6.1802***
	(0.0504)	(0.1471)	(0.1527)	(0.2326)	(0.2081)
Year Dummies		✓	✓	✓	✓
Sector Dummies		✓	✓	✓	✓
Regional Dummies		✓	✓	✓	✓
N	11269	11269	11269	6131	5138
R^2 adj.	0.001	0.325	0.327	0.318	0.338

Notes: Clustered standard errors at the individual level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Sensitivity of weight-penalty to different specifications of body size

	Women				Men			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BMI (weight/height^2)	-0.010***				0.0046**			
	(0.0019)				(0.0023)			
Weight in kilograms		-0.0037***				0.0017**		
		(0.0008)				(0.0008)		
Height in centimeters		0.0091***				0.0064***		
		(0.0017)				(0.0015)		
ln(BMI)			-0.2679***				0.1431**	
			(0.056)				(0.0632)	
Normal weight as reference								
Underweight ($BMI < 18.5$)				0.0486				-0.1458
				(0.0877)				(0.1187)
Overweight ($25 \leq BMI \leq 29.9$)				-0.0273				0.0396**
				(0.0192)				(0.0186)
Obese ($BMI > 29.9$)				-0.1097***				0.0333
				(0.0244)				(0.0248)
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Sector Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Regional Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Mincer Controls	✓	✓	✓	✓	✓	✓	✓	✓
Family Background	✓	✓	✓	✓	✓	✓	✓	✓
N	5138	5138	5138	5138	6131	6131	6131	6131
R^2 adj.	0.338	0.341	0.338	0.337	0.318	0.323	0.318	0.318

Notes: Clustered standard errors at the individual level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Panel and IV estimates for the relationship between body size and logarithm of hourly wage

	Women				Men			
	(1) FE	(2) RE	(3) IV-FE	(4) IV-RE	(5) FE	(6) RE	(7) IV-FE	(8) IV-RE
A: Models using BMI as weight measure								
BMI	0.0011	-0.0112***	-0.0947**	-0.1388***	0.0074***	0.0079***	0.0174	0.0186***
	(0.0031)	(0.0016)	(0.0412)	(0.014)	(0.0027)	(0.0016)	(0.0266)	(0.0104)
F first stage			24.294	194.671			51.507	279.15
Prob. > F			0.0000	0.0000			0.0000	0.0000
N	7667	7667	5246	7667	10879	10879	7928	10879
B: Models using Obese as weight measure								
Obese	0.0065	-0.0729***	-0.9441***	-1.3541***	0.0213	0.0238	1.2562	2.2494***
	(0.0285)	(0.018)	(0.3457)	(0.1373)	(0.0212)	(0.0154)	(0.8643)	(0.524)
F first stage			29.906	221.368			5.067	27.28
Prob. > F			0.0000	0.0000			0.0244	0.0000
N	7667	7667	5246	7667	10879	10879	7928	10879

Notes: Covariates included are age, schooling, experience, marital status and year dummies. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: OB decomposition of log of hourly wage: Obese vs non-obese

	Same controls		Controlling for presenteeism/absenteeism				Controlling for risk aversion				Controlling for crowding	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Women	Men	Women Without P&A	Women With P&A	Men Without P&A	Men With P&A	Women Without RA	Women With RA	Men Without RA	Men With RA	Women	Men
$\ln(w_{mean}^{NO})$	7.055***	7.123***	7.126***	7.126***	7.222***	7.222***	6.826***	6.826***	6.888***	6.889***	7.055***	7.123***
	(0.013)	(0.012)	(0.014)	(0.014)	(0.013)	(0.013)	(0.02)	(0.02)	(0.016)	(0.016)	(0.013)	(0.012)
$\ln(w_{mean}^{O})$	6.908***	7.163***	6.951***	6.951***	7.206***	7.206***	6.607***	6.607***	6.933***	6.935***	6.908***	7.163***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)	(0.035)	(0.035)	(0.034)	(0.034)	(0.022)	(0.022)
$\ln(w_{mean}^{NO}) - \ln(w_{mean}^{O})$	0.147***	-0.04	0.175***	0.175***	0.016	0.016	0.219***	0.219***	-0.045	-0.045	0.147***	-0.04
	(0.026)	(0.025)	(0.027)	(0.027)	(0.027)	(0.027)	(0.04)	(0.04)	(0.037)	(0.037)	(0.025)	(0.025)
Explained part	0.050***	-0.028*	0.076***	0.078***	0.001	0.001	0.113***	0.112***	-0.016	-0.019	0.084***	-0.022
	(0.016)	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)	(0.028)	(0.028)	(0.022)	(0.022)	(0.018)	(0.015)
Unexplained part	0.098***	-0.012	0.099***	0.097***	0.014	0.014	0.106***	0.107***	-0.028	-0.027	0.064***	-0.018
	(0.022)	(0.021)	(0.024)	(0.024)	(0.024)	(0.024)	(0.035)	(0.035)	(0.031)	(0.031)	(0.021)	(0.021)
N	5138	6131	3620	3620	3949	3949	2150	2150	3036	3049	5138	6131

Notes: The variables used as controls correspond to those used in Table 2. Clustered standard errors at the individual level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Crowding and wage-gap: Obese vs non-obese

	(1) Women	(2) Women	(3) Women	(4) Men	(5) Men	(6) Men
Obese	-0.096***	-0.064***	-0.232***	0.011	0.017	0.078
	(0.022)	(0.021)	(0.079)	(0.021)	(0.021)	(0.078)
Crowding		-0.039***	-0.040***		-0.011***	-0.010***
		(0.002)	(0.002)		(0.003)	(0.003)
Obese x Crowding			0.008**			-0.003
			(0.003)			(0.004)
Year Dummies	✓	✓	✓	✓	✓	✓
Sector Dummies	✓	✓	✓	✓	✓	✓
Regional Dummies	✓	✓	✓	✓	✓	✓
Mincer Controls	✓	✓	✓	✓	✓	✓
Family Background	✓	✓	✓	✓	✓	✓
N	5138	5138	5138	6131	6131	6131
R^2 adj.	0.337	0.408	0.408	0.317	0.320	0.320

Note: The variables used as controls correspond to those used in Table 2. Clustered standard errors at the individual level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: OB decomposition of log of hourly wage: Obese vs non-obese women by occupational categories

	(1) White collar (HS)	(2) White collar (LS)	(3) Blue collar (HS)	(4) Blue collar (LS)
$\ln(w_{mean}^{NO})$	7.660***	6.942***	6.686***	6.670***
	(0.021)	(0.015)	(0.032)	(0.016)
$\ln(w_{mean}^{O})$	7.476***	6.890***	6.676***	6.675***
	(0.05)	(0.031)	(0.064)	(0.027)
$\ln(w_{mean}^{NO}) - \ln(w_{mean}^{O})$	0.184***	0.052	0.011	-0.005
	(0.054)	(0.034)	(0.07)	(0.031)
Explained part	0.005	-0.01	-0.046	-0.027
	(0.029)	(0.017)	(0.052)	(0.017)
Unexplained part	0.179***	0.062**	0.056	0.023
	(0.052)	(0.031)	(0.054)	(0.028)
N	1315	2107	230	1475

Note: The variables used as controls correspond to those used in Table 2. Clustered standard errors at the individual level. HS = High Skilled and LS = Low Skilled. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: OB decomposition of log of hourly wage: Obese vs non-obese men by occupational categories

	(1) White collar (HS)	(2) White collar (LS)	(3) Blue collar (HS)	(4) Blue collar (LS)
$\ln(w_{mean}^{NO})$	7.878***	7.148***	6.972***	6.879***
	(0.028)	(0.02)	(0.018)	(0.013)
$\ln(w_{mean}^{O})$	7.805***	7.209***	7.091***	6.967***
	(0.059)	(0.039)	(0.043)	(0.026)
$\ln(w_{mean}^{NO}) - \ln(w_{mean}^{NO})$	0.073	-0.061	-0.119**	-0.088***
	(0.064)	(0.043)	(0.046)	(0.028)
Explained part	0.044	-0.042**	-0.051**	-0.050***
	(0.039)	(0.02)	(0.026)	(0.017)
Unexplained part	0.028	-0.019	-0.068*	-0.038
	(0.055)	(0.041)	(0.041)	(0.024)
N	986	1272	1472	2368

Note: The variables used as controls correspond to those used in Table 2. Clustered standard errors at the individual level. HS = High Skilled and LS = Low Skilled. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.