International Journal of Management Economics and Business, Vol. 17, No. 3, 2021
Uluslararası Yönetim İktisat ve İşletme Dergisi, Cilt 17, Sayı 3, 2021

Research Article / *Araştırma Makalesi*

OBESITY AND EMPLOYMENT: EVIDENCE FROM TURKEY

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ABSTRACT

Obesity is a devastating health condition that may harm employment. We investigate the impact of obesity on employment by utilizing five waves of Turkey Health Surveys and executing two different methods, including a multivariate logistic regression and a prominent matching method, entropy balancing. Turkey Health Surveys are representative of Turkey's adult population and have been conducted biennially since 2008. The surveys involve data collection using face to face interviews. In this study, we examine the differences in the relationship between obesity and employment by gender. We also shed light on whether the correlation between obesity and employability strengthened or weakened between 2008 and 2016. Descriptive analyses show that only 16% of obese females are employed while 70% of obese males are employed. Both methods suggest that obesity reduces employment for females. However, for males, there is no statistically significant relationship. Obesity significantly reduces female employment for all age groups except for younger cohorts, while for male employment, the results do not appear to provide a meaningful relationship. The significant interaction terms for obesity by year suggest that the negative effect of obesity on employment weakened overtime in Turkey.

Keywords: *Obesity, Employment, Gender, Matching Method.*

OBEZİTE VE İSTİHDAM: TÜRKİYE ÖRNEĞİ

ÖZET

Obezite, istihdama zarar verebilecek yıkıcı bir sağlık durumudur. Türkiye Sağlık Araştırmaları anketlerinden yararlanarak ve doğrusal olmayan bir olasılık modeli ve öne çıkan bir eşleştirme yöntemi olan entropi dengeleme dahil olmak üzere iki farklı yöntemi uygulayarak obezitenin istihdam üzerindeki etkisini araştırmaktayız. Türkiye Sağlık Araştırmaları Türkiye'deki yetişkin bireyleri temsil etmekte ve 2008 yılından bu yana her iki yılda bir yapılmaktadır. Anketler yüzyüze görüşme şeklinde veriler toplanarak uygulanmaktadır. Bu çalışmada, obezite ve istihdam arasındaki ilişkinin cinsiyete göre farklılıklarını incelemekteyiz. Ayrıca, obezite ve istihdam arasındaki korelasyonun 2008 ve 2016 yılları arasında kuvvetlenip kuvvetlenmediğine ışık tutulmaktadır. Betimsel analizler obez kadınların sadece yüzde 16'sının; obez erkeklerin ise yüzde 70'inin istihdam edildiğini göstermektedir. İki metod da obezitenin kadın istihdamını azalttığını göstermektedir. Ancak erkek istihdamı için istatistiksel olarak anlamlı bir ilişki söz konusu değildir. Obezite, genç nüfus dışında tüm yaş grupları için kadın istihdamını önemli ölçüde azaltırken, erkek istihdamı için sonuçlar anlamlı bir ilişki sağlamamaktadır. Yıllara göre obezite etkileşim terimleri, obezitenin istihdam üzerindeki olumsuz etkisinin zayıfladığını göstermektedir.

Anahtar Kelimeler: *Obezite, İstihdam, Cinsiyet, Eşleştirme Metodu.*

www.ijmeb.org ISSN:2147-9208 E-ISSN:2147-9194
http://dx.doi.org/10.17130/ijmeb.804066
Received: 02.10.2020, Accepted: 09.02.2021

1. Introduction

Obesity is a growing epidemic across the world (Mokdad et al., 1999:1520). According to the World Health Organization (WHO), the prevalence rate of obesity worldwide almost tripled between 1975 and 2016. Recent WHO global estimates in 2016 indicate that more than 1.9 billion adults (18+) were overweight, and of these, 650 million adults were obese (World Health Organization, 2008). These numbers correspond to about 39% and 13% of the adult population globally being overweight and obese in 2016, respectively.

Obesity can lead to numerous diseases, including type 2 diabetes, hypertension, stroke, coronary heart disease, arthritis, and cardiovascular diseases (Abbott et al., 1994:2370; Renna & Thakur, 2010:406; Jia, 2002:157; Mokdad et al., 2003:76). Besides, obesity is also causing indirect (non-medical) costs, which are associated with disability, absenteeism, workers' compensation, and presenteeism (i.e., one is going to work while she/he is sick, and this results in reduced productivity) (Devaux & Sassi, 2015:10). A critical study reviews the recent literature on the relationship between obesity and indirect costs. They include 31 studies in their analysis, where it is shown that the non-medical cost of obesity is changing from \$77 to \$1033 per obese person dependent upon the level of obesity (Trogdon et al., 2008:491).

Overweight and obesity were once considered high-income country problems, but now they are threatening the health of all, including low- and middle-income countries. For many decades, it is well known that most low- and middle-income countries have been struggling to prevent infectious diseases. While they continue to face these problems, they are now experiencing a rise in non-communicable disease risk factors such as obesity and overweight. According to the WHO Global Health Observatory Data Repository, overweight and obesity estimates for adults (20+) for Turkey in 2008 were about 62% and 28%, respectively (World Health Organization, 2013). Also, obesity prevalence forecast models suggest that 51% of men and 25% of women will be obese by 2030 in Turkey. All this evidence suggests that obesity has to be paid great attention soon in Turkey.

Morris (2007) lists four reasons why we would expect a correlation between obesity and employment. First, obesity may cause unemployment, which can happen for two reasons. We know that obesity is a debilitating health condition, giving rise to obese individuals being less productive than their non-obese counterparts. Therefore, they are less likely to be employed. The other reason why obesity may cause unemployment is that there can be employer-based discrimination against obese individuals, arising from employers' distaste towards obese workers, a belief that obese people are less productive, and uncertainty about obese people whether they will be productive. Second, unemployment can cause obesity by eating more less quality food. Third, there could be some unobserved factors that may be correlated both with obesity and employment at the same time. The final reason obesity and employment could be related is that low-income individuals can over-report their BMI so that the respondent's obesity status will be measured with error (Morris, 2007:415).

In this paper, we study the effect of obesity on employment likelihood in terms of the differences in the relationship between obesity and employment by gender. We run the analyses using five waves of Turkish Health Surveys conducted by the Turkish Statistical Institute (TurkStat) every two years since 2008. We exploit two distinct methods: first, we implement a multivariate logit estimation methodology to analyze the effect of obesity on employment. Second, we take advantage of a prominent matching method, entropy balancing, a multivariate reweighting method detailed in Hainmueller (2012), to investigate the impact of obesity.

There exists abundant research related to the labor market outcomes of obese individuals in developed countries. Caliendo & Gehrsitz (2016), using semiparametric regression models, find that obese females employed in white-collar jobs face lower wages. Also, underweight males employed in blue-collar sectors experience lower payments due to lack of muscular strength (Caliendo & Gehrsitz, 2016:210). Morris (2007) finds a causal relationship between obesity and employment for males and females in England (Morris, 2007:426). Cawley (2004) indicates that weight gives rise to fewer wages for white females in the US (Cawley, 2004:457). Caliendo & Lee (2013) find a negative relationship between being obese and being employed for women in Germany (Caliendo & Lee, 2013:122). Greve (2008), using a Danish panel survey, indicates a negative impact of BMI on employment prospects for women (Greve, 2008:354). Numerous international studies examine the effect of obesity on employment participation and earnings and found mixed results (Renna & Thakur, 2010:410; Norton & Han, 2008:10; Mosca, 2013:530; Tunceli et al., 2006:1643; Larose et al., 2016:31; Kinge, 2016:121; Hughes & Kumari, 2017:22; Caliendo & Lee, 2013:122).

Although abundant studies investigate the link between obesity and its determinants and employment outcomes in developed nations, the literature provides insufficient evidence for developing countries. Bhurosy & Jeewon (2014) indicate that BMI trends between 1999 and 2008 reveal an increase in most regions of the developing world (Bhurosy & Jeewon, 2014:3). Huffman & Rizov (2007) examine obesity and its determinants in Russia. Another study urges policymakers to address the prevention of dietary challenges faced by developing nations and the developed world (Popkin et al., 2012). Prentice (2005) focuses on the impacts of subsidized agriculture and cheap oils, affordable modern transportation, and television on weight gain in traditional nations.

Few studies in Turkey address what factors determine obesity (Hatemi et al., 2003; Yumuk, 2005; Karaoglan & Tansel, 2018). İşeri & Arslan (2008) examine the differences in obesity prevalence by regions, age groups, and genders. Erem et al. (2004), on the other hand, study the prevalence of obesity and its relationship with demographic, socioeconomic, and lifestyle factors in a city in Turkey.

In short, the studies on this subject are concentrated on developed countries, and clearly, there are a limited number of studies on Turkey's issue. Our contribution to the literature is threefold. First, we examine the impact of obesity on Turkey's employment prospects by implementing two distinct methods to understand the correlation between obesity and employment thoroughly. Second, we include more recent and nationwide data in our analysis, covering almost ten years from 2008 through 2016, which is very important because the obesity prevalence is growing, so studying employment issues caused by obesity over more extended periods became very important. Finally, Turkey introduced various types of precautions against obesity as part of health system changes. Therefore, this study will provide policy recommendations on whether new reforms targeting obesity helped in obese individuals' employment problems.

The results suggest that obesity affects females by reducing their employment significantly, while for males, there does not seem to exist a statistically significant outcome. In the meantime, for the age group 15-24, there are no statistically significant results. Exploiting a matching-based method, entropy balancing, yields similar results to those found utilizing the multivariate logistic regression.

The following section explains data and methods in detail. The third section will analyze the results and discussion. In the fourth section, discussion and concluding remarks will be explained.

2. Materials and Methods

In this study, we use pooled data from five rounds of Turkish Health Surveys (THS) conducted by TurkStat. The datasets are nationally representative surveys for the non-institutionalized Turkish population of all ages, implemented in 2008, 2010, 2012, 2014, and 2016. The structure of the THSs is cross-sectional, so for each survey, a new sample is drawn and interviewed. The THS provides information on socioeconomic and demographic indicators, general health, employment status, height, and weight measures, which we utilize to calculate BMI. In all regressions, we limit our sample to individuals aged between 15 and 64 years old. We also keep potential outliers out of the sample by restricting the sample to include only individuals with BMI above 15 and below 50 (Atella et al., 2008:308).

The primary variable in this study is current obesity, which we find using self-reported height and weight variables for each respondent in the THS. We define current obesity as a discrete variable, which equals 1 if individuals have a BMI higher than or equal to 30 kg/m^2, and 0 otherwise. The outcome of interest, employment, is a discrete variable equal to 1 if individuals are employed and 0 if individuals are unemployed. We keep all individuals aged 15-64 in the sample for our analyses. Using this sample, we assign 1 to individuals who state they are employed and 0 to individuals who state they are unemployed, including those out of the labor force.

We use a set of covariates for each respondent in the regression analyses. We control for the respondent's age and age squared to account for nonlinearity in all models. We also control for marital status, whether the person is married or single. We include household size and the number of kids in the household, and gender for individuals. We include general health status in all analyses as a binary variable as bad and good. We also include a variable that indicates whether the individual feels any physical pain as a binary variable. Educational attainment as a continuous variable indicating years of schooling is included in all models. Finally, survey year dummies for 2010, 2012, 2014, and 2016 (2008 being the reference year) and 26 statistical area dummies are included in the model.

Descriptive statistics by obesity status is in Table 1. It appears that 36% of obese individuals are employed in the full sample compared to non-obese by 44%. Notably, 62% of obese participants are female. 73% of non-obese people report that they are healthy, while 51% of obese people are saying they are healthy. Besides, the obese are more likely to have physical pain and less education.

It seems that there exist significant differences between obese and non-obese people. Therefore, controlling these differences in regression analyses will produce more reliable results. More importantly, only 16% of obese female individuals are employed, while 70% of obese males are employed.

In this study, we aim to assess the impact of obesity on adults' employment in Turkey. We employ two distinct methods to isolate the impact on employment prospects: a multivariate logistic estimation methodology and a matching estimator, entropy balancing (EB). We also implement some robustness checks using different cutoff points for the obesity variable to see whether the correlation between obesity and employment still holds. As for the first robustness check, *Obesity* variable takes the value 1 if the individual has a BMI higher than or equal to 32 kg/m2 and 0 otherwise. As other robustness, *Obesity* takes the value 1 if the individual has a BMI higher than or equal to 28 kg/m2 and 0 otherwise and rerun the analysis implementing these two methods.

Table 1: Descriptive Statistics by Obesity Status

	Full sample		**Female**		**Male**	
Obesity status	Non-Obese	Obese	Non-Obese	Obese	Non-Obese	Obese
Employed	0.440 (0.496)	0.364 (0.481)	0.241 (0.428)	0.161 (0.367)	0.651 (0.477)	0.698 (0.459)
Age	35.826 (13.487)	45.765 (10.985)	34.973 (13.118)	46.235 (10.874)	36.728 (13.809)	44.994 (11.123)
Married	0.659 (0.474)	0.865 (0.341)	0.661 (0.473)	0.850 (0.357)	0.656 (0.475)	0.890 (0.313)
Household size	3.802 (1.729)	3.494 (1.593)	3.781 (1.747)	3.446 (1.653)	3.823 (1.708)	3.573 (1.485)
Number of kids	0.964 (1.186)	0.818 (1.093)	1.015 (1.215)	0.796 (1.107)	0.909 (1.153)	0.854 (1.069)
Female	0.514 (0.500)	0.622 (0.485)	-	-	-	-
Good health	0.729 (0.445)	0.508 (0.500)	0.687 (0.464)	0.422 (0.494)	0.773 (0.419)	0.652 (0.477)
Physical pain	0.407 (0.491)	0.576 (0.494)	0.464 (0.499)	0.667 (0.471)	0.346 (0.476)	0.426 (0.495)
Education (in years)	8.451 (4.493)	6.562 (4.268)	7.949 (4.627)	5.437 (3.814)	8.982 (4.283)	8.409 (4.330)
Observations	62,467	14,402	32,089	8,951	30,378	5,451

Notes: Means are reported for continuous variables. Standard deviations in parenthesis. Percentages are reported for dummy variables.

2.1. Entropy Balancing Motivation and Scheme

Matching estimators rely on the conditional independence assumption, which implies that all variables that influence treatment assignment and potential outcomes simultaneously are observed (Caliendo & Koepining, 2008:35). One significant aspect of matching methods is to provide covariate balance before analyzing treatment effects. To obtain a balance in the covariate distributions, one usually goes back and forth between matching, balance checking, and propensity score estimation, which is not easy to do manually.

We employ a matching technique to solve the endogeneity issue, but matching is naturally done based on observable factors. However, the concern lies with unobservable factors here. There could be possible biases introduced as a result of omitted factors that may affect both the person's employability and obesity. For example, the literature on obesity discusses time-preference as an essential factor affecting both employment and obesity, producing a spurious correlation between the two variables.

In this part, we take obese individuals and non-obese individuals for our analysis. The challenging part is to make these two groups similar based on their observable characteristics. Here, we implement entropy balancing (EB), a reweighting technique, and focus on balancing observable variables, introduced by Hainmueller (2012).

Suppose we have randomly drawn samples of $n1$ treated and $n2$ control units from a population of $N1$ and $N2$ respectively, where $n1 \leq N1$ and $n2 \leq N2$. Let $Di = 1$ if unit i is treated and $Di = 0$ if unit i is in the control group. We also let X be a vector of J pre-treatment control variables such that $X_i = [X_{i1}, X_{i2}, ..., X_{ij}]$. The density functions of the covariates in the treated and control groups are given by $f_{X|D=1}$ and $f_{X|D=0}$ respectively. $Y_i(D_i)$ shows the pair of potential outcomes for unit i based on treatment and control conditions, following the potential outcome framework for causal inference. Observed outcomes are given by $Y = Y(1)D + Y(0)(1-D)$.

Population average treatment effect on treated (PATT) is given by $\tau = E[Y(1) \mid D=1] - E[Y(0) \mid D=$. The first expectation's estimates in the previous formula can be obtained from the treated. However, the second expectation is the counterfactual. Rosenbaum & Rubin (1983) indicate that assuming selection on observables, $Y(0) \perp D \mid X$, and overlap, $\Pr(D=1 \mid X=x) <$ for all x in the support of $f_{(X|D=1}$, the PATT is identified as:

$$\tau = E[Y \mid D=1] - \int E[Y \mid X=x, D=0] f_{X|D=1}(x)\, dx \tag{1}$$

The second term in Equation 1 needs to be estimated. The covariate distribution in the comparison group will be adjusted to make it similar to that of the treatment group to reduce the imbalance in the covariate distributions between the two groups. We could utilize a variety of matching methods to do this. Once the covariate distributions are adjusted, regression methods will estimate treatment effects (Imbens, 2004; Rubin, 2006).

Propensity score weighting (Hirano & Imbens, 2001; Hirano et al., 2003) is one of the methods to estimate the mean for counterfactual, which is estimated as

$$E[Y(0) \mid D=1] = \frac{\sum_{\{i|D=0\}} Y_i d_i}{\sum_{\{i|D=0\}} d_i} \tag{2}$$

Each unit in the comparison group takes a weight given by $d_i = \frac{\hat{p}(x_i)}{1-\hat{p}(x_i)}$. $p(x_i)$ is a propensity score generally estimated by a probit or logistic regression of the treatment status on the covariates. If the propensity score model is specified correctly, then the estimated d_i will provide balanced covariate distribution in the comparison and treatment groups. However, in general, because of the propensity score model's misspecification, this practice fails, and the researcher must go back and forth between logistic and probit regression, weighting, and balance checking to seek for weighting that would balance the covariate distribution in both comparison and treatment groups.

Entropy balancing, however, estimates the weights directly from a large set of balance constraints. The counterfactual mean in entropy balancing can be estimated by

$$E[Y(0) \mid D=1] = \frac{\sum_{\{i|D=0\}} Y_i w_i}{\sum_{\{i|D=0\}} w_i} \tag{3}$$

where w_i is the entropy balancing weight for each control unit. The following reweighting scheme will be applied to choose weights by minimizing the entropy balancing distance metric:

$$\min_{w_i} H(w) = \sum_{\{i|D=0\}} w_i \log\left(\frac{w_i}{q_i}\right) \tag{4}$$

subject to normalizing and balance constraints

$$\sum_{\{i|D=0\}} W_i C_{ri}(X_i) = m_r \quad with\; r\, \varepsilon\, 1, \ldots, R \;\; and \tag{5}$$

$$\sum_{\{i|D=0\}} W_i = 1 \;\; and \tag{6}$$

$$W_i \geq 0 \; f\,or\; all\; i \;\; such\; that \;\; D=0 \tag{7}$$

where $q_i = 1/n_0$ is a base weight and $c_{ri}(X_i) = m_r$ describes *R* balance constraints (Hainmueller & Xu, 2013).

Here, covariates that will be included in the reweighting process are chosen in the first stage of the entropy balancing. It is possible to define different sets of balance constraints in Equation 5 to make the moments (mean- first moment, variance- second moment, skewness- third moment) of the covariate distribution in the reweighted comparison and treatment groups.

Then, entropy balancing will search for a set of unit weights $W = [W_i, \ldots, W_{n2}]^T$ that would minimize Equation 4, the entropy distance between W and the vector of base weights $Q = [q_i, \ldots, q_{n2}]^T$, subject to the balance constraints in Equation 5, the normalization constraints in Equation 6, and the non-negativity constraint in Equation 7, which ensures that the weights are adjusted as far as is needed to accommodate the balance constraints, but at the same time, the weights are kept as close as possible to the uniformly distributed base weights to retain information in the reweighted data.

In contrast to the complicated procedure of propensity score methods, EB seems more effective in reducing covariate imbalance by preprocessing the control group's covariate distribution (non-obese) to make it more similar to that of the treatment group (obese) by reweighting. It utilizes a preprocessing method where the weight function includes the covariate balance. In the present analysis, after entropy balancing, we want the control (non-obese) to have the same mean and the same variance of all the conditioning variables as in the treatment (obese).

3. Empirical Results

Tables 2-3 contain our main findings. We first run a multivariate logistic regression for employment, controlling a set of covariates. Column 1 of Table 2 presents the full sample results, controlling for age and its square, household size, number of kids, marital status, gender, health status, physical pain, survey year dummies, education in years, and 26 statistical area dummies. It shows that obesity significantly reduces employment prospects by 3 ppt for the full sample. Column 2 of Table 2 indicates a large and well-defined effect on females' employment by 5 ppt while we do not see any significant impact on males.

According to the results, age shows an inverse-U relationship with employment likelihood, indicating that employment starts declining at some age. Married women are less likely to be employed, which is expected in Turkey because men are seen as the primary breadwinner. Therefore, when females get married, even if they have a job, they are more likely to drop their employment to take care of the housework, such as cleaning, cooking, and raising the kids. On the contrary, married men are more likely to be employed than single men, which also supports our argument about the role of men seen as the primary breadwinner in Turkey. The number of kids seems to reduce female employment, consistent with the female role in Turkey. Related to the number of kids at home, even if a female is not married, they are supposed to look after their baby brothers or sisters at home, which might explain the relationship between the number of kids and employment. It also seems that education increases employment probability for both men and women.

Furthermore, year dummies, capturing differences associated with the time covered, show that employment probability increased for the years 2014 and 2016 in Turkey. However, the time trend for employment probability indicates more substantial results for women compared to men. Most importantly, the significant interaction terms for obese by year suggest that the negative impact of obesity on the likelihood of employment has been weakened over time in Turkey, indicating that obese individuals are more likely to be employed over the years (see the appendix, Table 6).

Then, we implement a prominent matching method, Entropy Balancing, to isolate the effect of obesity on the probability of employment by controlling pre-treatment characteristics of the treatment and the comparison groups. Findings indicate that the coefficients are similar to those obtained using a multivariate logistic regression estimator for various models.

Table 2: The Impact of Obesity on Employment by Gender: Logit and Entropy Balancing

Logit Model-Marginal Effects	**Full sample (1)**	**Females (2)**	**Males (3)**
Obese	-0.031^{***} (0.004)	-0.047^{***} (0.005)	-0.003 (0.006)
Age	0.067^{***} (0.001)	0.045^{***} (0.001)	0.068^{***} (0.001)
Age squared	-0.001^{***} (0.000)	-0.001^{***} (0.000)	-0.001^{***} (0.000)
Married	0.017^{***} (0.005)	-0.064^{***} (0.005)	0.169^{***} (0.007)
Household size	0.004^{**} (0.001)	0.008^{***} (0.002)	-0.005^{***} (0.002)
Number of kids	-0.009^{***} (0.002)	-0.032^{***} (0.003)	0.016^{***} (0.003)
Female	-0.353^{***} (0.002)	-	-
Good health	0.048^{***} (0.004)	0.016^{***} (0.005)	0.079^{***} (0.005)
Physical pain	0.011^{***} (0.003)	0.013^{***} (0.004)	0.008^{*} (0.005)
Education (in years)	0.015^{***} (0.000)	0.018^{***} (0.000)	0.007^{***} (0.001)
2010	-0.005 (0.006)	0.008 (0.007)	-0.011 (0.008)
2012	-0.003 (0.005)	0.009 (0.006)	-0.004 (0.007)
2014	0.030^{***} (0.005)	0.043^{***} (0.007)	0.029^{***} (0.007)
2016	0.022^{***} (0.005)	0.045^{***} (0.007)	0.009 (0.008)
Observations	76,823	41,017	35,806
Entropy balancing			
Obese	-0.024^{***} (0.005)	-0.045^{***} (0.005)	0.003 (0.007)
Observations	76,823	41,017	35,806

Notes: Robust standard errors in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. *We cluster standard errors at the household level for the logit model. Linearized standard errors in parenthesis for entropy balancing. We keep all individuals aged 15-64 in the sample for analyses. We drop potential outliers with BMI below 15 and above 50. We utilize data from 2008, 2010, 2012, 2014, and 2016. Individual-level control variables are included in all specifications for age, age squared, marital status, household size, number of kids, gender, health status, physical pain, survey year dummies, education in years, and 26 statistical area dummies. The dependent variable is a binary variable taking the value 1 if the individual is employed 0 otherwise. Obesity is a discrete variable taking the value of 1 if the respondent has* a BMI higher than or equal to 30 kg/m^2 *and 0 otherwise. After reweighting, the control group has the same mean and the same variance as the treatment group.*

Table 3 presents the estimates to see the differential impacts of obesity on the probability of being employed for different age groups. Two significant results emerge from Table 3. None of the models show statistically significant results for the age group 15-24, irrespective of gender or methods chosen. When we analyze the prevalence of obesity by age groups, we find that age cohorts 15-24 reveal a lower prevalence of obesity (3.5%), explaining the findings. Both methods provide significant evidence that obesity harms employment for the rest of the age groups in females. Another significant outcome from Table 3 is that estimations do not produce statistically significant evidence on the effect of obesity on employment prospects for males.

Table 3: The Impact of Obesity on Employment by Age Groups: Logit and Entropy Balancing

Full sample	**(15-24)**	**(25-34)**	**(35-44)**	**(45-54)**	**(55-64)**
Logit model-Marginal Effects	-0.017	-0.037***	-0.018***	-0.024***	-0.041***
	(0.016)	(0.009)	(0.007)	(0.008)	(0.009)
Entropy balancing	-0.025	-0.041***	-0.024***	-0.024***	-0.039***
	(0.019)	(0.012)	(0.009)	(0.009)	(0.008)
Observations	15,992	17,548	17,435	15,074	10,774

Females	**(15-24)**	**(25-34)**	**(35-44)**	**(45-54)**	**(55-64)**
Logit Model-Marginal Effects	-0.013	-0.050***	-0.045***	-0.041***	-0.054***
	(0.019)	(0.014)	(0.011)	(0.009)	(0.009)
Entropy balancing	-0.013	-0.044***	-0.043***	-0.040***	-0.048***
	(0.020)	(0.012)	(0.010)	(0.009)	(0.009)
Observations	8,532	9,748	9,445	7,763	5,387

Males	**(15-24)**	**(25-34)**	**(35-44)**	**(45-54)**	**(55-64)**
Logit Model-Marginal Effects	0.013	-0.003	0.013	0.007	-0.021
	(0.027)	(0.013)	(0.008)	(0.012)	(0.016)
Entropy balancing	0.017	-0.005	0.013	0.008	-0.019
	(0.031)	(0.012)	(0.008)	(0.013)	(0.016)
Observations	7,460	7,800	7,990	7,311	5,245

Notes: Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. *We cluster standard errors at the household level for the logit model. Linearized standard errors in parenthesis for entropy balancing. We keep all individuals aged 15-64 in the sample for analyses. We drop potential outliers with BMI below 15 and above 50. We utilize data from 2008, 2010, 2012, 2014, and 2016. Individual-level control variables are included in all specifications for age, age squared, marital status, household size, number of kids, gender, health status, physical pain, survey year dummies, education in years, and 26 statistical area dummies. The dependent variable is a binary variable taking the value 1 if the individual is employed 0 otherwise. Obesity is a discrete variable taking the value of 1 if the respondent has* a BMI higher than or equal to 30 kg/m^2 *and 0 otherwise. After reweighting, the control group has the same mean and the same variance as the treatment group.*

Outcomes significantly differ by gender. We can explain this vast difference by occupation sectors, in which females and males are employed. For example, males may be more employed in blue-collar jobs where masculine strength is of great importance. Therefore, being obese may not be an issue in terms of productivity or look. However, for females, if they work in a service industry where people care about physical appearance, obesity may be a problem in finding a job in this sector.

3.1. Sensitivity Analysis

We check the robustness of our results by changing the BMI threshold for obesity because the BMI is constructed based on self-reported height and weight measures. Table 4 reports the full sample and gender-based results. *Obesity* takes the value 1 if the BMI is higher than or equal to 32 kg/m2. All methods produce similar results between obesity and employment, where the highest impact comes from the female subpopulation.

Table 4: The Impact of Obesity on Employment by Gender-Robustness Analysis - BMI>=32

	Full sample	Females	Males
Logit model-Marginal Effects	-0.036*** (0.005)	-0.048*** (0.006)	-0.006 (0.008)
Entropy balancing	-0.030*** (0.005)	-0.045*** (0.005)	-0.002 (0.008)
Observations	76,823	41,017	35,806

Notes: Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. *We cluster standard errors at the household level for the logit model. Linearized standard errors in parenthesis for entropy balancing. We keep all individuals aged 15-64 in the sample for analyses. We drop potential outliers with BMI below 15 and above 50. We utilize data from 2008, 2010, 2012, 2014, and 2016. Individual-level control variables are included in all specifications for age, age squared, marital status, household size, number of kids, gender, health status, physical pain, survey year dummies, education in years, and 26 statistical area dummies. The dependent variable is a binary variable taking the value 1 if the individual is employed 0 otherwise. Obesity is a discrete variable taking the value of 1 if the respondent has* a BMI higher than or equal to 32 kg/m^2 *and 0 otherwise. After reweighting, the control group has the same mean and the same variance as the treatment group.*

In table 5, the *Obesity* variable is defined as a discrete variable taking the value 1 if the respondent's BMI is higher than or equal to 28 kg/m2, which is a further robustness check taking measurement error into account. Results yield similar outcomes as before, which suggests that the measures are robust to various BMI cutoff choices.

Table 5: The Impact of Obesity on Employment by Gender-Robustness Analysis - BMI>=28

	Full sample	Females	Males
Logit model-Marginal Effects	-0.029*** (0.003)	-0.049*** (0.005)	-0.001 (0.005)
Entropy balancing	-0.023*** (0.004)	-0.046*** (0.005)	0.005 (0.005)
Observations	76,823	41,017	35,806

*Notes: Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. We cluster standard errors at the household level for the logit model. Linearized standard errors in parenthesis for entropy balancing. We keep all individuals aged 15-64 in the sample for analyses. We drop potential outliers with BMI below 15 and above 50. We utilize data from 2008, 2010, 2012, 2014, and 2016. Individual-level control variables are included in all specifications for age, age squared, marital status, household size, number of kids, gender, health status, physical pain, survey year dummies, education in years, and 26 statistical area dummies. The dependent variable is a binary variable taking the value 1 if the individual is employed 0 otherwise. Obesity is a discrete variable taking the value of 1 if the respondent has* a BMI higher than or equal to 28 kg/m^2 *and 0 otherwise. After reweighting, the control group has the same mean and the same variance as the treatment group.*

4. Discussion

In this study, we implement a multivariate logit estimation methodology and a prominent matching estimator, entropy balancing, to measure the impact of obesity on Turkey's employment using a rich dataset. We find large and well-defined impacts of being obese on female individuals' employment status, consistent with the literature (Caliendo & Gehrsitz, 2016:30; Cawley, 2004:457; Caliendo & Lee, 2013:122; Greve, 2008:354). In the meantime, there seems to be no association between male employment and obesity. To the best of our knowledge, this is the first study investigating the impact of obesity on employment in Turkey.

Obesity is a debilitating health condition that may cause one to lose her job. The economic theory suggests that obesity and unemployment may be correlated in a way that obesity causes unemployment. There could be two channels to explain how this relationship works: First, obese people are possibly less productive than non-obese people, so they are more likely to be unemployed. Second, there could be a channel through which discrimination works by employers (Balsa & McGuire, 2003:93).

Studying the relationship between obesity and employment in a country where universal health coverage has been in effect since 2008 will provide lessons to similar countries in designing policies for obese individuals' employment. Besides, Turkey offers free primary care and emergency care to all citizens without charging their employers. Employers do not have to pay high premiums for their obese employees when they need to receive costly treatments or operations. Therefore, there is no way that employers will incur a higher cost by employing obese individuals concerning higher health care bills. Therefore, employers' hiring decisions will not contain discrimination based on uncertainty about obese individuals' healthcare costs. However, there could still be other channels through which employers may discriminate against potential obese employees in their hiring decisions. For example, employers may have little information about obese individuals' productivity, leading to uncertainty-based discrimination (Pagan & Davila, 1997). Besides, discrimination in hiring based on health reasons is not likely to be eliminated by introducing universal health coverage. Employers will still factor in costs of on-the-job training, absences from work, and turnover. Universal health coverage may mitigate but not eliminate issues related to the health needs of obese workers.

This study has some limitations. Our econometric approaches do not yield any causal link between obesity and employment. Instead, the results should be treated as correlations. We cannot observe factors that might affect employment and obesity or reverse causation between employment and obesity. There are limitations in using BMI to measure obesity, as different obesity measures may reveal different results (Johansson et al., 2009). Another limitation is that the data does not contain information about the occupation and the industrial sector employed individuals are working.

Notwithstanding limitations, this study offers significant findings. We observe from our analysis that there are significant differential impacts of obesity in terms of gender, which can be explained by different occupations in which females and males are employed. In Turkey, females are mostly hired in service sectors where the physical appearance is of particular importance to employers and customers. Therefore, discriminating may occur through this channel here. We do not see any relationship between male employment and obesity because males are employed mostly in blue-collar jobs where being obese might mean one can overcome heavy duties.

To sum up, while there does not appear to exist any impact of being obese on males' employment, it appears that females are the ones who are facing a significant amount of reduction in their employment due to obesity in Turkey. Also, the impact of obesity on employment has been weakened over time in Turkey. The results also leave room for further research to identify the type of discrimination and in which sectors this might be happening, and to what extent it plays a significant role in losing employment.

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Appendix

Table 6: The Impact of Obesity on Employment by Gender: Linear Probability Model and Entropy Balancing

Linear probability model	Full sample	Females	Males
Obese	-0.060*** (0.010)	-0.065*** (0.012)	-0.035** (0.016)
Age	0.066*** (0.001)	0.041*** (0.001)	0.088*** (0.001)
Age squared	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)
Married	0.006 (0.005)	-0.076*** (0.006)	0.177*** (0.008)
Household size	0.003* (0.001)	0.008*** (0.002)	-0.002 (0.002)
Number of kids	-0.004* (0.002)	-0.024*** (0.003)	0.006* (0.003)
Female	-0.407*** (0.003)	-	-
Good health	0.052*** (0.004)	0.019*** (0.005)	0.082*** (0.006)
Physical pain	0.011*** (0.003)	0.013*** (0.004)	0.007 (0.005)
Education (in years)	0.016*** (0.000)	0.022*** (0.001)	0.006*** (0.001)
2010	-0.007 (0.006)	0.006 (0.008)	-0.016* (0.009)
2012	-0.007 (0.005)	0.007 (0.007)	-0.012* (0.007)
2014	0.025*** (0.006)	0.038*** (0.008)	0.025*** (0.008)
2016	0.011* (0.006)	0.036*** (0.008)	-0.001 (0.008)
Obese x 2010	0.026* (0.014)	0.022 (0.016)	0.024 (0.023)
Obese x 2012	0.030** (0.012)	0.006 (0.014)	0.042** (0.019)
Obese x 2014	0.028** (0.013)	0.022 (0.015)	0.020 (0.020)

Table 6 continued

Obese x 2016	0.056*** (0.013)	0.038** (0.015)	0.053** (0.021)
Observations	76,823	41,017	35,806
Entropy balancing			
Obese	-0.019 (0.013)	-0.048*** (0.013)	-0.010 (0.019)
Observations	76,823	41,017	35,806

*Notes: Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. We cluster standard errors at the household level for the linear probability model. Linearized standard errors in parenthesis for entropy balancing. We keep all individuals aged 15-64 in the sample for analyses. We drop potential outliers with BMI below 15 and above 50. We utilize data from 2008, 2010, 2012, 2014, and 2016. Individual-level control variables are included in all specifications for age, age squared, marital status, household size, number of kids, gender, health status, physical pain, survey year dummies, education in years, 26 statistical area dummies, and the interaction term between survey year dummies and obesity status. The dependent variable is a binary variable taking the value 1 if the individual is employed 0 otherwise. Obesity is a discrete variable taking the value of 1 if the respondent has* a BMI higher than or equal to 30 kg/m^2 *and 0 otherwise. After reweighting, the control group has the same mean and the same variance as the treatment group.*