Canadian Journal of Public Health (2018) 109:873–881
https://doi.org/10.17269/s41997-018-0097-7

QUANTITATIVE RESEARCH

The effect of body weight on employment among Canadian women: evidence from Canadian data

Nazmi Sari[1] · Beliz Acan Osman[2]

Received: 8 December 2016 / Accepted: 31 May 2018 / Published online: 13 June 2018

Abstract
Objectives This paper examines the impact of obesity on labour market participation among Canadian women by using various Canadian population health surveys.
Methods We estimate the impact of obesity on labour market participation using probit and bivariate probit regression models. To correct for a potential endogenous relationship between obesity and labour market participation, we also use instrumental variables in the bivariate probit regression context.
Results The results suggest that the probability of employment has negative association with the body weight of women. This effect is statistically significant and has substantial impact on employment. The results show that obesity decreases employment probability by about 25 percentage points for women.
Conclusion In addition to well-known negative health consequences, obesity also has additional negative effect on employment. This negative impact on employment is comparable to the impacts of mental health or illicit drug use on employment. Public health policies aimed at reducing obesity would generate additional benefits to society. Our results also provide additional evidence for lawmakers to amend the labour laws in Canada in order to acknowledge and prohibit hiring practices that discriminate against individuals with high body weight.

Résumé
Objectifs Examiner les incidences de l'obésité sur la participation au marché du travail des femmes canadiennes à l'aide de diverses enquêtes canadiennes sur la santé des populations.
Méthode Nous estimons les incidences de l'obésité sur la participation au marché du travail à l'aide des modèles de régression probit et probit bivarié. Pour corriger une possible relation endogène entre l'obésité et la participation au marché du travail, nous utilisons aussi des variables instrumentales dans le contexte de la régression probit bivariée.
Résultats Les résultats indiquent que la probabilité d'emploi est négativement associée au poids des femmes. Cet effet est significatif et a des incidences considérables sur l'emploi. Selon les résultats obtenus, l'obésité réduit la probabilité d'emploi d'environ 25 points de pourcentage chez les femmes.
Conclusion Outre ses conséquences négatives bien connues sur la santé, l'obésité a un effet néfaste sur l'emploi. Cet effet sur l'emploi est comparable à celui des problèmes de santé mentale ou de la consommation de drogue. Les politiques de santé publique qui visent à réduire l'obésité présenteraient donc des avantages supplémentaires pour la société. Nos résultats offrent aussi aux législateurs de nouvelles données à l'appui de la modification de la législation ouvrière au Canada pour reconnaître et interdire les pratiques discriminatoires envers les personnes de poids élevé.

Keywords Obesity · Body weight · Employment · Probit/biprobit regression · Health survey

✉ Nazmi Sari
Nazmi.Sari@usask.ca

[1] Department of Economics, University of Saskatchewan, 9 Campus Drive, Arts 815, Saskatoon, SK S7N 5A5, Canada

[2] Saskatchewan Health Quality Council, Saskatoon, SK S7N 5A5, Canada

Mots-clés Obésité · Poids du corps · Emploi · Régression probit/biprobit · Enquêtes de santé

Introduction

Obesity is an important public health issue that affects several countries around the world. As it is consistently shown in the literature, it is a major risk factor for a number of chronic diseases (World Health Organization 2017). In addition to the literature examining its negative health effects (World Health Organization 2017), there is also a growing literature investigating the association between bodyweight and its labour market consequences (Cawley 2004; Morris 2006, 2007). This literature suggests that obese individuals may face discrimination in the workplace that can take place in every stage from selection to placement, compensation, and promotion (Hamermesh and Biddle 1994; Brunello and D'Hombres 2007). It may arise from stereotyping by employers, and/or prejudices against obese people that may create workplace discrimination from employers or even customers (Roehling 1999). This literature also suggests that obesity could be associated with poor labour market outcomes arising from a belief that the obese individuals are less productive in workplaces (Everett 1990).

The association between obesity and labour market outcomes in the form of wage penalties or lack of employment opportunities has been extensively studied (Averett and Korenman 1996; Baum and Ford 2004; Cawley et al. 2009; Cawley 2000a; Cawley 2004; Garcia and Quintana-Domeque 2006; Norton and Han 2008; Morris 2006, 2007). These studies conclude that obesity decreases the probability of employment and wages for both men and women while it has a more pronounced impact for women. Within this large body of literature, a relatively small number of studies focus on the impact of obesity on employment/unemployment, with considerable variations in their methodology and data sets used. As indicated in this literature, due to reverse causality or omitted variable bias, obesity can be endogenous for labour market outcomes. However, some papers in this literature attempt to deal with endogeneity of obesity (Morris 2007; Hamermesh and Biddle 1994), while others do not tackle this issue (Klarenbach et al. 2006; Tunceli et al. 2006).

Our aim in this paper is to study the impact of obesity on labour market participation among women by using a panel data set from Canada. In this paper, we take the endogeneity into account and examine the differences in employment participation associated with obesity. While we cannot identify the sources or mechanisms through which discrimination may exist, our purpose is to estimate the size of employment participation differential associated with obesity. Given that there is no study within the Canadian context, our study will fill an important gap in the literature. We start with a probit regression, and then explore bivariate probit models and instrumental variable (IV) estimations in bivariate probit context in order to correct for potential endogenous relationship between obesity and labour market participation.

Methods

Data source

As a primary data set, we use the Canadian National Population Health Survey (NPHS). The NPHS is a biennial panel survey started in 1994. It is representative of the Canadian population, designed to measure health determinants and health status of Canadians. It also includes labour market outcomes, socio-economic and demographic characteristics of the participants, and the postal codes of their residences (Statistics Canada 2017).

In addition to the NPHS, we use additional data sets. For local labour market conditions and socio-economic characteristics, we use the 2006 Canadian Census. To deal with any endogeneity of obesity remaining after we exploit the panel structure of the data, we use IVs. To create the IVs, we use the Canadian Community Health Survey (CCHS) Cycle 3.1 and the Desktop Mapping Technologies Inc. (DMTI) Spatial Enhanced Points of Interest (EPOI) database. The details about the IVs are discussed in the section "Instrumental variables."

The CCHS 3.1 is a cross-sectional health survey conducted in 2005. It includes geographical identifiers and a wide range of variables measuring health behaviour and health status of Canadians. The CCHS is used to create region-specific prevalence of obesity.

The DMTI provides a national database of over 1.6 million Canadian business and recreational points of interest. It assigns highly accurate latitude and longitude coordinates and has detailed standard industrial classification (SIC) codes for each business and recreational point of interest. Using detailed SIC codes, the EPOI file explicitly classifies the physical exercise and fitness facilities, membership sports and recreation clubs, and golf courses. This data set is available for all provinces. We use 2006 data from the DMTI and create a variable measuring the distance to the closest physical fitness and exercise facility.

Study sample

In the regression analysis discussed in the section "Instrumental variables," we use data from three cycles (cycles 6–8) of the NPHS collected in 2004/2005, 2006/2007, and 2008/2009. We restrict the sample to the individuals aged 20–59 (inclusive) in cycle 8 who have responded to the survey for three cycles and live in a Census Metropolitan Area (CMA) or a tracted Census

Agglomeration Area (CA). We drop observations with missing values for body mass index (BMI) and employment status. Pregnant women are also excluded from the sample because of the effect of pregnancy on individuals' weight.

Dependent and independent variables

Table 1 presents definitions, means (or share), and standard deviations for all the variables used in the regression analyses. We use employment status to measure individuals' labour force participation. This measure is a dummy variable indicating whether the respondent worked at a job or business at least an average of 10 h a week. We also use 20 h as an alternative cutoff point to check the sensitivity of the results to our definition of employment.

BMI, body weight in kilogram (kg) divided by the height in metres squared (m^2), is used as a measure for obesity. Following the obesity literature, a dummy variable indicating individuals with BMI greater than 30 is used as a variable for obesity.

Socio-economic and demographic characteristics affect individuals' participation in the labour market as well as their body weight. In order to control for potential omitted variable bias from these sources, we include rich sets of explanatory variables in the estimations. These are income, education, household composition, and other demographic characteristics such as marital status and age. It is also likely that differences in ethnic and racial background may influence obesity as well as the labour market outcomes. To account for these factors, immigrant and minority status are also included in the regressions. Since any differences in health status may also affect the labour market outcomes, we include variables for self-reported health status and chronic conditions to deal with this issue. We also include area-specific factors (population size, education and unemployment rate, percent of occupied

Table 1 Summary statistics for individual, regional, and instrumental variables

Variable name	Variable description	Mean/proportion	S.D.	Data source
Individual-level continuous variables				
Age	Age of the respondent	38.997	10.4291	NPHS 6
HH size	Household size	3.0764	1.3178	NPHS 6
Children	Number of kids aged < 12 in the household	0.5289	0.8802	NPHS 6
Income	Total household income in $10,000	7.3683	5.0192	NPHS 6
Chronic	Number of chronic conditions	1.5302	1.57617	NPHS 6
tee	Energy expenditure from physical activities	1.9546	1.78041	NPHS 6
Individual-level dichotomous variables				
Employed	Worked in a job/business 10+ hours/week	0.8075	0.3940	NPHS 8
Obese	Body mass index higher than 30	0.1906	0.39292	NPHS 7
Married	Married or had a common law partner	0.6123	0.4874	NPHS 6
Immigrant	Immigrant	0.0809	0.2727	NPHS 6
Minority	Visible non-Aboriginal minority	0.0436	0.2044	NPHS 6
High school	Secondary school graduates	0.4121	0.4924	NPHS 6
College	University/college graduates	0.5160	0.4999	NPHS 6
Poor health	Self-perceived health: poor or fair	0.0603	0.23818	NPHS 6
Stressful	Self-perceived stress: quite a bit or extreme	0.2786	0.4484	NPHS 6
Regional variables (census subdivision level)				
Ln population	Logarithm of population aged 24–65	9.220	1.475	Census
Dwellings occupied	Private dwellings occupied by usual residents, in 10,000 dwellings	2.429	7.424	Census
University (%)	University degree aged 25–64 (%)	22.79	11.09	Census
College (%)	College degree aged 25–64 (%)	21.83	4.16	Census
Male unemployed (%)	Male unemployment rate aged 25+ (%)	5.03	3.96	Census
Female unemployed (%)	Female unemployment rate aged 25+ (%)	4.90	2.93	Census
Instrumental variables				
Obese (%)	Census subdivision level obesity (%)	15.7	8.7	CCHS
Distance to PA facility	Minimum distance in km to any physical fitness/exercise facility in 2006	1.62	2.33	DMTI

The values shown in column 3 represent the mean for continuous and proportion for categorical variables. *S.D.* stands for standard deviation. The sample size is 1558 for the NPHS variables. *NPHS*, National Population Health Survey; *Census*, 2006 Canadian Census data; *CCHS*, Canadian Community Health Survey Cycle 3.1; *DMTI*, Spatial Enhanced Points of Interest database created by the Desktop Mapping Technologies Inc.

private dwellings) which measure local labour market conditions and other socio-economic characteristics affecting participation decision and body weight.

Instrumental variables

As described in the next section, instrumental variables have been used within the context of bivariate probit model when there is any endogeneity problem. A valid IV has to have a strong correlation with individual-level obesity and not to be correlated with error terms in the bivariate model. If the IVs are weakly correlated with obesity, then even a weak correlation between the IVs and the errors can lead to a large inconsistency in the IV estimates (Bound et al. 1995).

Earlier studies have identified several IVs for obesity. For instance, area-level average BMI and prevalence of obesity have been used as IVs in papers by Morris (Morris 2006, 2007). Consistent with these studies, we use the prevalence of obesity as one of the IVs that is computed from the CCHS 3.1 by census subdivision in which the individuals live.

In addition, we also use the distance to the closest physical fitness, sports, and exercise facilities. We compute the distance to the facilities using geographical coordinates for facilities and the postal codes of the individuals' residences. Although the DMTI database provides precise geographical coordinates for facilities, the geographical coordinates for individuals' place of residence have not been provided in the NPHS. However, we can obtain the geographical coordinates for individuals using individuals' six-character postal codes and the Postal Code Conversion File (PCCF) that provides a linkage between the postal codes and latitude and longitude coordinates representing an approximate point location for the corresponding postal code. The PCCF provides precise geographical coordinates for postal codes in urban areas, but they are not precise in other types of regions. For instance, civic addresses are not available for some postal codes such as those associated with rural routes. Many of these postal codes tend to overlap several dissemination areas and often cross boundaries of standard geographic areas such as census tracts or census subdivisions. In order to overcome this issue, as indicated in the section "Study sample," we restrict the sample to individuals who live in the CMAs and the CAs.

We use social interaction literature to determine the IVs mentioned above. This literature suggests that the presence of social interactions will induce a tendency for conformity in behaviour (Manski 2000; Brock and Durlauf 2001). As suggested by Bernheim (1994), due to potentially strong consumption complementarities, individuals conform to follow similar behaviour even though they may have heterogeneous preferences. Social interaction also plays a role in defining individuals' preferences related to health behaviours such as healthy eating and exercising. There is considerable evidence in the literature that individual body weight is influenced by health behaviours of the local population (Christakis and Fawler 2007). Hence, we expect that the proximity to the physical activity facilities and prevalence of obesity are correlated with the individual obesity, and not necessarily correlated with labour force participation decisions. These assumptions are tested in the Results section.

Bivariate probit regression analyses

There are various sources for obesity to be endogenous for labour market outcomes. One of the sources can be due to reverse causality or simultaneity bias. As obesity affects labour market outcomes, it is likely that labour market outcomes such as unemployment may affect obesity since unemployed individuals are more likely to consume inexpensive food such as processed meat, fries, snacks, and sweets. Inexpensive foods are high in refined grains, added sugars, and added fats compared to healthy alternatives (Drewnowski and Barratt-Fornell 2004). As a result, longer unemployment may lead to higher body weight. Owing to the potential impact of unemployment on obesity, obesity coefficient of employment/unemployment regressions will be biased in an empirical model in which simultaneity bias has not been corrected. Another source of endogeneity is the omitted variable bias in the labour participation equation. Even after dealing with the simultaneity bias, one can still expect that obesity may remain endogenous due to omitted variables.

As a solution to the simultaneity bias, we exploit the panel structure of the data by measuring labour market outcome, obesity, and other independent variables, including health status in different cycles of the panel survey. By following this approach used in an earlier paper (Sari 2014), we use data from the last three cycles of the NPHS and measure all control variables at cycle 6 (2004), obesity at cycle 7 (2006), and labour market outcome at cycle 8 (2008). We also condition the regressions to the baseline employment status.

In order to control for potential bias originating from omitted variables, we include rich sets of covariates in the model. This approach would provide a solution to the endogeneity issue if there are no unobserved factors affecting obesity and labour market participation decision. However, this assumption is very strong given that social and physical environments are important factors influencing health, education, and labour market outcomes (WHO Commission on Social Determinants of Health n.d). Even after including a set of covariates, it is likely to have additional unobserved social and physical determinants of health affecting both labour market and health outcomes of individuals. In addition to these factors, earlier studies also point out the possibility of additional unobserved factors, such as time preferences, that may affect both obesity and labour market participation decisions of the individuals (Morris 2007; Norton and Han 2008; Brown et al. 2005; Cawley 2000b).

Due to potentially joint unobservable factors as described above, we estimate obesity and labour market participation equations jointly. Following the earlier literature, the impact of obesity on labour market participation is estimated using a bivariate regression model as defined below:

$$L_{i,C} = \beta_0 + \beta_1 O_{i,C-1} + \beta_2 X_{i,C-2} + \varepsilon_{1i} \tag{1}$$

$$O_{i,C-1} = \alpha_0 + \alpha_1 X_{i,C-2} + \varepsilon_{2i} \tag{2}$$

where subscript C stands for the NPHS cycle 8.

In the model above, L_i stands for labour market participation of individual i. O_i is a dummy variable for obese individuals, and the matrix X_i includes socio-economic and demographic factors and health measures, as well as baseline labour market participation. It is also likely that the socio-economic environment in which individuals live influences their lifestyle and labour market participation decisions. Therefore, we also include local labour market outcomes, education level, and other population characteristics using the 2006 Canadian Census.

In this bivariate model, the error terms, ε_{1i} and ε_{2i}, are assumed to have a bivariate normal distribution with a covariance of $Cov(\varepsilon_{1i}, \varepsilon_{2i}) = \rho$. The covariance term captures the unobserved factors affecting both obesity and labour market outcome. If this term becomes statistically insignificant, then the model above can be estimated separately using a univariate probit model rather than a bivariate model. In other words, one can use a test of $\rho = 0$ as an exogeneity test for the obesity variable in labour market participation equation (Greene 2000). However, a statistically significant covariance term implies that the obesity in the labour market participation equation is endogenous, suggesting that we need to use IVs within the context of the bivariate model defined above. The results from our estimations from each method described above are presented in the Results section.

Results

We estimate a probit model for Eq. (1), then we estimate the model in Eqs. (1) and (2) using a bivariate probit model. Based on a final sample size of 1558 individuals, we present a summary of the results from these regressions in Table 2. The full results are presented in Appendix Tables 4 and 5.

In Table 2, we present the estimated coefficient and marginal effect for the obesity variable. Following Norton and Han (2008), we create an employment variable using weekly hours of work. Models 1 and 3 present the regression results when we use 10 h/week or more as the definition of employment. Alternatively, we also use 20 h/week or more as a benchmark, and present the results in models 2 and 4.

Table 2 shows that as probit regression indicates positive and significant coefficients, the bivariate probit results indicate negative and statistically significant results. These results, therefore, indicate that the choice of the empirical strategy is important. We use a Wald test to see if the participation and obesity equations need to be estimated separately (Wooldridge 2002). The results show that the error terms are positively correlated, and the test indicates that the bivariate assumption is valid in this framework. However, the significant covariance term which captures the unobserved factors affecting both obesity and labour market outcome implies that the obesity variable in the labour market participation equation is not exogenous. This suggests that an IV approach in the context of bivariate probit model needs to be used.

In order to tackle the endogeneity of the obesity variable in the bivariate model defined above, we use IVs in the context of bivariate probit regressions. Models 1a and 2a show results with one IV (proximity to physical fitness and sports facilities) while models 1b and 2b show the results when we include both IVs (proximity measure and prevalence of obesity). These results are presented in Table 3.

Table 3 shows that the error terms are positively and significantly correlated. The Wald test indicates that covariance term is significant. We introduce the two IVs mentioned above to tackle the endogeneity issue. Both instruments have expected positive signs and are jointly significant in the obesity equation. The Wald test suggests that as the distance to the closest physical fitness and sports facilities increases, individuals are more likely to be obese.

The second condition for the validity of IVs is that they should have no direct impacts on labour market participation other than their impact through obesity. To verify this, we perform an overidentification test to show that the IVs are validly excluded from the labour market participation equation. Following Guilkey and Lance (2014), we perform a likelihood ratio (LR) test of a null hypothesis that the coefficients for IVs are jointly zero in the labour market participation equation. The Chi-square value for the LR test is 0.04 (p value > 0.98), suggesting that the null hypothesis cannot be rejected, therefore these IVs

Table 2 Impact of obesity on employment: bivariate and univariate probit

	Probit				Bivariate probit			
	Model 1		Model 2		Model 3		Model 4	
	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
Obese	0.341 (0.003)	.0734 (0.003)	0.230 (0.027)	0.0616 (0.026)	− 0.964 (0.030)	− 0.2257 (0.042)	− 0.827 (0.142)	− 0.2279 (0.149)
ρ					0.6735		0.5669	
χ^2 for $\rho = 0$					5.489 (0.019)		2.546 (0.111)	
N	1558		1558		1558		1558	

ME stands for marginal effects for the obesity variables. *p* values are reported in parentheses. The dependent variable is a dummy variable indicating whether the individual is in paid employment. In model 1 and model 3, the dependent variable equals to 1 if the individual works an average of 10 or more hours in a week. In other models, we use 20 h/week as a benchmark

are valid and properly excluded from the labour market participation equation.

Our results show that the effect of obesity on employment status for women is negative and statistically significant in all models. When we introduce the IV approach in bivariate probit models, the marginal effects have changed by about 3 percentage points compared to the results presented in Table 2. However, the overall conclusion is very similar. As indicated by the marginal effects in Table 3, obese women are about 25 percentage points less likely to be employed than non-obese women. This overall conclusion aligns well with the literature. For instance, Morris (2007) states that obese women are 21 percentage points less likely to be employed than their non-obese counterparts.

Discussion

We estimate the impact of obesity on employment probability for women in Canada. As indicated in bivariate specifications, the positive sign of the correlation coefficient between error terms in both obesity and employment participation equations

Table 3 Impact of obesity on employment: bivariate IV probit

	Model 1a		Model 1b		Model 2a		Model 2b	
	Coeff	ME	Coeff	ME	Coeff	ME	Coeff	ME
Impact of the obesity on employment								
Obese	− 1.058 (0.003)	− 0.2490 (0.005)	− 1.052 (0.003)	− 0.2476 (0.005)	− 0.935 (0.026)	− 0.2581 (0.028)	− 0.931 (0.025)	− 0.2569 (0.027)
ρ	0.7162		0.7143		0.62163		0.6205	
χ^2 for $\rho = 0$	9.230 (0.002)		9.366 (0.002)		5.135 (0.023)		5.197 (0.023)	
Impact of the instruments on obesity								
Distance to PA facility	0.0330 (0.044)		0.0357 (0.031)		0.0314 (0.058)		0.0343 (0.040)	
Obese (%)			1.363 (0.066)				1.371 (0.067)	
χ^2 for $I = 0$	4.05 (0.044)		7.43 (0.024)		3.58 (0.058)		7.06 (0.029)	
N	1558		1558		1558		1558	

ME stands for marginal effects for the obesity variables. *p* values are reported in parentheses. The dependent variable is a dummy variable indicating whether the individual is in paid employment. In models 1a and 1b, the dependent variable equals to 1 if the individual works an average of 10 or more hours in a week. In other models, we use 20 h/week as a benchmark. *I = 0* stands for joint significance of the instruments in obesity equation suggests the existence of the unobserved factors affecting both employment probability and obesity. We dealt with the endogeneity using the IVs in the bivariate probit framework. Our IV bivariate probit models indicate a significantly negative impact of obesity on employment. This impact is not only statistically significant but also quite substantial (a decrease in employment probability by about 25 percentage points). As it is the case with any survey-based study, there are potential limitations (i.e., reporting bias, and recall errors associated with self-reported data, measurement error of BMI measure) that the readers should take into account when interpreting these results.

This estimated impact reported above is comparable or even higher than the impact of, for instance, mental health or illicit drug use on labour market participation. There is a large body of literature focusing on the impact of mental health on labour market participation that indicates a detrimental effect of mental health on labour market outcomes. The size of the effect differs across studies, but as summarized by Frijters and his colleagues (Frijters et al. 2010), it is in the range of a 14 to 26 percentage point reduction (for Latino females) in labour market participation associated with psychiatric disorder, or a 19 percentage point reduction due to depression. Our estimated negative impact of obesity on employment is also comparable to the impact of illicit drug use that suggests a 27–35 percentage point reduction in employment probability due to marijuana use, or a 32–41 percentage point reduction due to cocaine use (DeSimone 2002). These comparable estimates suggest that the negative effect of obesity on labour market participation is no different than other health priorities which have consistently received similar or higher level of attention from the policy makers and researchers. Our results, therefore, suggest that successful health policies towards reducing obesity would generate additional benefits by reducing inequities that may have resulted from discrimination based on body weight.

Our main finding presented above is in line with the evidence of labour market discrimination based on body weight shown in studies from laboratory and field settings. In this literature, studies examining the effect of body weight and other factors for discrimination suggest that discrimination in hiring based on body weight is greater than discrimination associated with race, sex, or particular disabilities (Roehling 1999). This literature and our finding imply that, in addition to sex-based discrimination, obese women face additional bias due to their body weight; therefore, the labour market participation gap between men and women is significantly larger for obese women. Our results in this paper provide important evidence for policy makers around policy priorities to reduce inequities resulting from discrimination based on body weight.

There are rules and regulations around the world attempting to achieve equal pay between men and women (Government of Canada 2018). While necessary, those policies are insufficient in dealing with inequity as long as discrimination in hiring continues to exist. Even if these equal pay policies become successful in achieving equal wages between men and women, they will be insufficient given that the individuals facing discriminatory practices in hiring need to have better qualifications than their counterparts in order to be hired in the first place. This implies that these individuals are in fact paid less than what they should have been based on their qualifications. It is, therefore, essential to have public policies specifically focusing on rules and regulations prohibiting discrimination in the hiring process.

Despite the evidence of discrimination in workplaces, so far there are no antidiscrimination laws prohibiting discrimination based on body weight in hiring (Puhl et al. 2015). Other than a few exceptions in local jurisdictions in the US, many countries, including Canada, have no national laws that specifically prohibit discrimination based on body weight (Puhl et al. 2015). The Canadian Human Rights Act prohibits discrimination based on race, national or ethnic origin, colour, religion, age, sex, sexual orientation, marital status, family status, or disability, but it does not prohibit discrimination based on body weight (Government of Canada 2018). Based on results in our paper and in the related literature, and given the rising rates of obesity around the globe, antidiscrimination laws need to acknowledge and prohibit discriminatory practices against individuals with high body weight. There is already significant public support in countries, including the US and Canada, for specific labour laws prohibiting discrimination based on body weight in workplaces (Puhl et al. 2015). It is therefore timely to amend antidiscrimination labour laws to reduce inequities resulting from this type of discrimination.

Acknowledgements Over the course of my (NS) academic career, many individuals have inspired me by their tremendous energy, inspiration, dedication, and belief for social justice and equity. Among many, I would like to especially thank and acknowledge Mr. and Mrs. Ismet and Nursen Metin for their lifelong dedication and hard work as well as their strong belief in public service to improve the lives of disadvantaged and vulnerable populations.

Appendix

Table 4 Full results from probit and bivariate probit regression models

	Probit regression	Bivariate probit regression	
	Employment equation	Employment equation	Obesity equation
Obese	0.341	−0.964	
	(0.003)	(0.030)	
Age	−0.016	−0.012	0.012
	(0.001)	(0.007)	(0.006)
Married	0.103	0.075	0.070
	(0.310)	(0.442)	(0.470)
Immigrant	0.153	0.081	−0.345
	(0.390)	(0.641)	(0.043)
Aboriginal	−0.202	0.081	0.602
	(0.599)	(0.842)	(0.102)
HH size	−0.008	−0.010	−0.006
	(0.852)	(0.806)	(0.887)
Children	0.020	0.009	−0.014
	(0.731)	(0.865)	(0.802)
Minority	−0.235	−0.270	−0.304
	(0.269)	(0.193)	(0.209)
Income	0.012	0.008	−0.019
	(0.260)	(0.446)	(0.043)
High school	0.301	0.268	−0.021
	(0.046)	(0.056)	(0.887)
College	0.354	0.303	−0.072
	(0.021)	(0.034)	(0.627)
Chronic	0.003	0.0456	0.124
	(0.916)	(0.114)	(0.000)
Poor health	−0.445	−0.204	0.347
	(0.007)	(0.292)	(0.025)
Stressful	0.087	0.107	0.097
	(0.372)	(0.241)	(0.255)
tee	0.003	−0.018	−0.100
	(0.889)	(0.416)	(0.000)
Employed (cycle 6)	1.435	1.333	0.138
	(0.000)	(0.000)	(0.194)
Ln population	−0.051	−0.052	0.011
	(0.190)	(0.158)	(0.758)
University (%)	0.001	−0.001	−0.010
	(0.827)	(0.834)	(0.088)
College (%)	−0.028	−0.031	−0.025
	(0.088)	(0.055)	(0.111)
Male unemployed (%)	−0.020	−0.019	0.002
	(0.387)	(0.389)	(0.925)
Female unemployed (%)	0.028	0.013	−0.063
	(0.361)	(0.637)	(0.019)
Dwellings occupied	0.0003	0.001	0.003
	(0.920)	(0.653)	(0.301)
Constant	1.078	1.388	−0.393
	(0.100)	(0.025)	(0.510)

The dependent variable for the employment equation equals to 1 if the individual works an average of 10 or more hours in a week. *p* values are reported in parentheses. For obesity equation, the dependent variable equals to 1 if the individuals have body mass index higher than 30. All models include region dummies

Table 5 Full results from bivariate IV probit regression models

	Employment equation	Obesity equation	Employment equation	Obesity equation
Obese	−1.058		−1.052	
	(0.003)		(0.003)	
Distance to PA facility		0.033		0.036
		(0.044)		(0.031)
Obese (%)				1.363
				(0.066)
Age	−0.012	0.012	−0.012	0.013
	(0.007)	(0.003)	(0.007)	(0.002)
Married	0.072	0.067	0.073	0.061
	(0.456)	(0.473)	(0.451)	(0.524)
Immigrant	0.078	−0.347	0.077	−0.340
	(0.653)	(0.042)	(0.655)	(0.046)
Aboriginal	0.104	0.622	0.101	0.616
	(0.795)	(0.092)	(0.800)	(0.093)
HH size	−0.011	−0.009	−0.011	−0.009
	(0.792)	(0.811)	(0.787)	(0.822)
Children	0.009	−0.011	0.010	−0.009
	(0.864)	(0.840)	(0.860)	(0.867)
Minority	−0.271	−0.293	−0.271	−0.282
	(0.190)	(0.227)	(0.190)	(0.245)
Income	0.007	−0.020	0.007	−0.020
	(0.458)	(0.040)	(0.458)	(0.038)
High school	0.265	−0.022	0.263	−0.029
	(0.057)	(0.878)	(0.059)	(0.840)
College	0.297	−0.074	0.295	−0.078
	(0.037)	(0.612)	(0.037)	(0.594)
Chronic	0.048	0.124	0.048	0.124
	(0.077)	(0.000)	(0.077)	(0.000)
Poor health	−0.183	0.341	−0.184	0.341
	(0.320)	(0.027)	(0.314)	(0.027)
Stressful	0.109	0.088	0.108	0.083
	(0.230)	(0.299)	(0.234)	(0.332)
tee	−0.019	−0.100	−0.019	−0.102
	(0.379)	(0.000)	(0.379)	(0.000)
Employed (cycle 6)	1.318	0.137	1.319	0.134
	(0.000)	(0.197)	(0.000)	(0.209)
Ln population	−0.052	0.033	−0.052	0.033
	(0.152)	(0.366)	(0.151)	(0.366)
University (%)	−0.001	−0.009	−0.001	−0.005
	(0.813)	(0.141)	(0.809)	(0.390)
College (%)	−0.030	−0.022	−0.030	−0.021
	(0.055)	(0.157)	(0.056)	(0.188)
Male unemployed (%)	−0.019	−0.001	−0.019	0.002
	(0.378)	(0.959)	(0.370)	(0.911)
Female unemployed (%)	0.013	−0.055	0.013	−0.059
	(0.641)	(0.042)	(0.633)	(0.032)
Dwellings occupied (%)	0.001	0.002	0.001	0.002
	(0.627)	(0.493)	(0.617)	(0.456)
Constant	1.398	−0.800	1.401	−1.135
	(0.022)	(0.200)	(0.022)	(0.084)

The dependent variable for the employment equation equals to 1 if the individual works an average of 10 or more hours in a week. *p* values are reported in parentheses. For obesity equation, the dependent variable equals to 1 if the individuals have body mass index higher than 30. All models include region dummies

References

Averett, S., & Korenman, S. (1996). The economic reality of the beauty myth. *Journal of Human Resources, 31*(2), 304–330.

Baum, C. L., & Ford, F. W. (2004). The wage effects of obesity: a longitudinal study. *Journal of Health Economics, 24*(2), 341–363.

Bernheim, B. D. (1994). A theory of conformity. *Journal of Political Economy, 102*(5), 841–877.

Bound, J., Jaeger, A. D., & Baker, M. R. (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variables is weak. *American Statistical Association, 90*(450), 443–450.

Brock, W. A., & Durlauf, S. N. (2001). Discrete choice with social interactions. *Review of Economics Studies, 68*(2), 235–260.

Brown, H. S., Pagan, J. A., & Bastida, E. (2005). The impact of diabetes on employment: genetic IVs in a bivariate probit. *Health Economics, 14*, 537–544.

Brunello, G., & D'Hombres, B. (2007). Does body weight affect wages? Evidence from Europe. *Economics Human Biology, 5*, 1–19.

Cawley, J. (2000a). An instrumental variables approach to measuring the effect of body weight on employment disability. *Health Services Research, 35*(5), 1159.

Cawley J. (2000b). Body weight and women's labor market outcomes. NBER working paper series. Working paper 7841.

Cawley, J. (2004). The impact of obesity on wages. *Journal of Human Resources, 39*(2), 451–474.

Cawley, J., Han, E., & Norton, E. C. (2009). Obesity and labor market outcomes among legal immigrants to the United States from developing countries. *Economics and Human Biology, 7*(2), 153–164.

Christakis, N. A., & Fawler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine, 357*(4), 370–337.

DeSimone, J. (2002). Illegal drug use and employment. *Journal of Labor Economics, 20*(4), 952–977.

Drewnowski, A., & Barratt-Fornell, A. (2004). Do healthier diets cost more? *Nutrition Today, 34*, 161–168.

Everett, M. (1990). Fat chance: let an overweight person call on your best customers? *Sales & Marketing Man, 42*(4), 66–70.

Frijters P, Johnston DW, Shields MA. (2010). Mental health and labour market participation: evidence from IV panel data models. IZA discussion paper no 4883

Garcia, J., & Quintana-Domeque, C. (2006). Obesity, employment and wages in Europe. *Advances in Health Economics & Health Services Research, 17*, 187–217.

Government of Canada.(2018) Canadian Human Rights Act. Current to 2018-02-15 and last amended on 2017-06-19. Available at: http://laws-lois.justice.gc.ca/eng/acts/h-6/page-1.html#h-5 (Accessed February 2, 2018).

Greene, W. H. (2000). *Econometric analysis*. Upper Saddle River: Prentice-Hall Inc.

Guilkey, D. K., & Lance, P. (2014). Program impact estimation with binary outcome variables: Monte Carlo results for alternative estimators and empirical examples. In R. C. Sickles & W. C. Horrace (Eds.), *Festschrift in honor of Peter Schmidt: econometric methods and applications* (pp. 5–46). NewYork: Springer Science and Business Media.

Hamermesh, D. S., & Biddle, J. E. (1994). Beauty and the labor market. *American Economic Review, 84*(5), 1174–1194.

Klarenbach, S., Padwal, R., Chuck, A., & Jacobs, P. (2006). Population-based analysis of obesity and workforce participation. *Obesity, 14*, 920–927.

Manski, C. F. (2000). Economic analysis of social interactions. *Journal of Economic Perspective, 14*(3), 115–136.

Morris, S. (2006). Body mass index and occupational attainment. *Journal of Health Economics, 25*(2), 347–364.

Morris, S. (2007). The impact of obesity on employment. *Labour Economics, 14*, 413–433.

Norton, E. C., & Han, E. (2008). Genetic information, obesity, and labor market outcomes. *Health Economics, 17*(9), 1089–1104.

Puhl, R. M., Latner, J. D., O'brien, K. S., Luedicke, J., Danielsdottir, S., & Salas, X. R. (2015). Potential policies and laws to prohibit weight discrimination: public views from 4 countries. *The Milbank Quarterly, 93*(4), 691–731.

Roehling, M. V. (1999). Weight-based discrimination in employment: psychological and legal aspects. *Personnel Psychology, 52*, 969–1017.

Sari, N. (2014). Sports, exercise and length of stay in hospitals: is there a differential effect for chronically ill people? *Contemporary Economic Policy, 32*(2), 247–260.

Statistics Canada.(2017) National population health survey. Available at: https://www.statcan.gc.ca/eng/survey/household/3225 (Accessed September 12, 2017).

Tunceli, K., Li, K., & Keoki Williams, L. (2006). Long-term effects of obesity on employment and work limitations among U.S. adults, 1986 to 1999. *Obesity, 14*(9), 1637–1646.

WHO Commission on Social Determinants of Health.(n.d.) Closing the gap in a generation: health equity through action on the social determinants of health: Commission on Social Determinants of Health final report. Geneva: WHO publications.

Wooldridge, J. M. (2002). *Econometric analysis of cross-section and panel data*. Cambridge: MIT Press.

World Health Organization. 2017 Obesity: preventing and managing the global epidemic. World Health Organization technical report series 894, 2000 Available at: http://libdoc.who.int/trs/WHO_TRS_894.pdf (Accessed November 10, 2017).