Obesity Based Labour Market Discrimination in South Africa: A Dynamic Panel Analysis

Junita Henry and Umakrishnan Kollamparambil

ERSA working paper 701

August 2017

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

Obesity Based Labour Market Discrimination in South Africa: A Dynamic Panel Analysis

Junita Henry*and Umakrishnan Kollamparambil†

August 23, 2017

Abstract

There is increasing concern regarding obesity related healthcare costs in South Africa. Obesity is also seen to have far reaching effects that seep into labour market outcomes (Barnett & Kumar, 2009). Using NIDS panel data, this study aims to examine the relationship between Body Mass Index and employment status as well as wage levels. This is done using a probit and tobit model and thereafter a system GMM model to take endogeneity into account. Thereafter, the paper uses ethnicity backed obesity thresholds to measure the discrimination obese individuals face on the probability of becoming employed and their wages earned once employed. It is found that obesity is indeed, an influencing factor and a source of discrimination within the labour market in South Africa. Moreover, this discrimination is seen to be more so for females than males.

Keywords: Obesity, Unemployment, Wages, Discrimination, labour market, South Africa

JEL codes: I14, J71, J31

1 INTRODUCTION:

Obesity has been on the rise in Africa and there is increasing evidence of its association with co-morbidities in the continent (Adeboye et al., 2012). According to studies, close to 40% of South African women are obese or overweight (Department of Health, 2015). Obesity not only markedly increases the rate of morbidity and mortality, but imposes a growing financial burden on individuals as well as the State (Fairbrother, 2009). Reports show that severe obesity is associated with a 23% increase in the use of healthcare (Tugendhaft & Hofman, 2014). It is with this in mind that the South African government is proposing the introduction of a sugar tax to aid in reducing diseases which put strain on the health care system (National treasury, 2016).

*School of Economic and Business Sciences, University of Witwatersrand, Johannesburg, South Africa. Email: junita.h13@gmail.com

†Associate Professor in Economics, School of Economic and Business Sciences, University of Witwatersrand, Johannesburg, South Africa. Email: uma.kollamparambil@wits.ac.za

Obesity also has an impact at an individual level through the labour market impact. The impact of obesity on employment status and wages can be a result of not only reduced productive capacity due sickness, ill health, lack of fitness to perform duties successfully and failure to pass medical standards (Barnett & Kumar, 2009); but also of employer prejudice and stereotyping (Harkonen, Rasanen, & Nasi, 2011). Several studies have been done on the impact of obesity on employment but the evidence has been mixed across countries and socioeconomic groups. Cawley (2004), Morris (2007), Johansson et al. (2009), Lindeboom et al. (2010) and Some et al. (2016) report evidence of a negative relationship between employment and obesity; with the relationship being stronger for females. On the other hand, Garcia & Quintana-Domeque (2006) and Cawley et al. (2008) do not find any significant relationship. Asgeirsdottir (2011) cements the diversity in findings by noting that the relationship between these variables depends on the racial composition of the population as well as the different political circumstances of a country.

Research that identifies the relationship between these variables has not been extensive in South Africa. Some et al. (2016), which replicated a study done in England by Morris (2007) using Wave 1 of the National Income Dynamics Study, is the only study in the South African context. Although the paper finds obesity to significantly reduce the probability of being employed in South Africa using a probit analysis, it does not attempt to analyse the impact of obesity on wage levels among the employed. Furthermore, the study does not quantify the discrimination against the obese. Also, the study does not take ethnicity-based obesity classification or the persistent nature of labour market characteristics into account. Although the paper does consider the issue of endogeneity, it does so by the use of external instruments which may pose potential problems as discussed in the next section.

This paper addresses the concerns raised against Some et al. (2016) by; firstly, taking ethnicity into account in determining obesity classification. Secondly, taking endogeneity into account by exploiting the use of panel data without the use of external instrument variables. Thirdly, using a dynamic panel estimation the study takes into account the persistent nature of labour markets. Lastly and most importantly, this paper analyses whether obesity is a potential source of socio-economic discrimination that South Africans face in the labour market. Furthermore, discrimination for males and females are separately quantified to gain insights into the gender dimension of the issue.

Although increasing levels of obesity in South Africa is acknowledged and fiscal measures are in the pipeline to address the issue, the impact of obesity at an individual level on the labour markets in South Africa has not received sufficient attention. The need for South African specific study is pertinent given the limited external validity of other studies as the cultural context is different in South Africa as highlighted by Wittenberg (2011). The contribution of the study is not limited to being South Africa specific alone. No study in the international context has been undertaken within the superior system GMM framework that accounts for endogeniety in an effective way. Moreover, international studies thus far have failed to take into account race specific thresholds in defining obesity, endogeniety and Oaxaca blinder decomposition within a single framework.

The findings of the study yield a consistent non-linear relationship between body mass index (BMI) and employment probability as well as wages. While initial increases in BMI leads to an increase in the probability of employment and wages, sustained increases turns this relationship negative. While substantial discrimination is observed against the obese in relation to both employment status as well as wages, discrimination is noted to be higher with regards to determining wage levels. A gender-wise analysis yields that obese women face greater discrimination compared to obese males.

The rest of the paper proceeds as follows: Section 2 will review existing literature, Section 3 considers the theoretical determinants and hypothesized relations. Section 4 looks at the descriptive statistics and Section 5 presents the methodology. Section 6 examines the relationship between obesity and labour market outcomes using multivariate regressions. The main contribution of this paper is discussed in Section 7, analysing the discrimination faced by the obese in the labour market using the Blinder-Oaxaca approach. The analysis is further broken down at the level of gender for both employment status and wages. Conclusions bring up section 7.

2 LITERATURE REVIEW

Numerous studies have realised the world-wide growing concern of obesity within their respective regions and acknowledge its potential impact on the labour market. Sargent & Blanchflower (1994) studied the effect of obesity on employment of young adults in Britain, using Ordinary Least Squares, and found significant results for females but insignificant results for males. Harper (2000) using a logit model also found insignificant results for males. Both papers defined obesity as Body Mass Index (BMI) restricted to respective percentiles of the sample distribution. The results were significant however when Sarlio-Lahteenkorva and Lahelma (1999) used a logit model and defined obesity as a BMI of greater than 30kg/m2. However, none of the above papers addressed the issue of the endogeneity between obesity and employment.

Endogeneity could be present through reverse causality between employment and obesity. While obesity may cause unemployment due to discrimination by the employer or decreased work capacity as a result of debilitating obesity-related health conditions, unemployment may also cause obesity because unemployed individuals are more likely to consume less expensive, more fattening food as a result of lower earnings. Furthermore, Wittenburg (2011) shows that within South African black households, a heavier weight is preferred and unemployed individuals tend to be lighter than those employed. Using instrument variables to account for endogeneity, Greve (2008) found a negative effect of BMI on employment for women and an inverted U-shaped effect for men in the private sector in Denmark. Whereas results from the public sector show that BMI has no influence on wages for either men or women.

Baum & Ford (2004) used variants of differenced regressions to control for endogeneity and show that obesity decreases wages more significantly for females. An investigation of the Swedish labour market done by Dackleburg et al. (2014), revealed the opposite. Individual fixed-effects results showed that there is a significant obesity wage-penalty for men but not for women. Although these results contest the findings of the majority of the literature, they are linked to and influenced by the diverse demographics across all countries as stated by Asgeirsdottir (2011).

Morris (2007) used a bivariate probit model to investigate the impact of obesity on employment to account for endogeneity. The study instruments obesity using obesity incidence within the area in which the respondent resides. This is a peer group effect which is a result of local population activity and social norms. The finding is that, in England, obesity has a negative and significant impact on employment for both males and females. Morris (2007) notes that endogeneity affects the estimates for women but not for men. The first major limitation to solving endogeneity using the instrument variable approach is in finding the suitable instruments.

Some et al. (2016) replicated Morris' (2007) paper using the same econometric model for South Africa using three instrument variables: the degree of physical activity, the obesity status of the respondent's head of household, and past diagnosis of an obesity-associated illness. The suitability of these instruments are questionable as it is possible that the degree of physical activity is related to employment and income levels, i.e. costly gym membership/ low income earners may walk more. Additionally, the obesity status of the head of household could affect individuals through peer effects examined by Morris and/or biological transmission, which is unrelated to employment. Cawley et al. (2005) use the weight of a family member as an instrument variable. However, research has shown that approximately 50% of the variation in BMI is a result of non-genetic factors such as an individuals' environment and their choices. Therefore, the variable may not be entirely exogenous (Cawley, 2004). Furthermore, diseases such as high or low blood pressure, heart problems, diabetes or stroke are highly correlated with obesity and may to some extent be correlated to employment.

Endogeneity can also be taken into account by the use of a dynamic Generalised Method of Moments (GMM) model. This method demands panel data, but the advantage of this method is that the use of autoregressive wage equations eliminates the omitted variable bias as well as individual fixed effects. Pinkston (2015) used the differenced GMM modelled by Holtz-Eakin et al. (1988) and Arellano and Bond (1995) to conduct his analysis on the US youth. He considered the effect of BMI on wages in the years following labour market entry. Pinkston's (2015) results show that obesity in women negatively affects their wages. However, according to Roodman (2009) the lagged dependent variable in Difference-GMM is still potentially endogenous and any predetermined explanatory variables that are not strictly exogenous become potentially endogenous. The Arellano–Bover/Blundell–Bond estimator, known as System GMM, augments Arellano–Bond Difference GMM estimation by including data in levels and making an additional assumption that ?rst di?erences of instrument variables are uncorrelated with the ?xed e?ects (Kollamparambil, 2016). The set-up of their estimator implies that the fixed effects are eliminated using first differences and an instrumental variable estimation of the differenced equation is performed. This study uses the one-step system GMM estimator addressing endogeneity more effectively.

Aside from endogeniety, another difficulty in empirical research comes in the form of measuring obesity. This will be discussed in detail in the methodology section. However, Wittenburg (2011) provides evidence that the use of BMI as a measure is legitimised in South Africa and can be used as an indicator. Literature lacks in taking ethnicity into account when classifying individuals as obese. Furthermore, Cawley (2004) rejected the hypothesis that all races are equal. His findings suggest that Hispanic and Black females experienced smaller penalties than White females.

Various studies argue that BMI is a flawed measure of obesity. However, the World Health Organisation outlines BMI as an adequate measure that "defines obesity and the associated risk to the development of health consequences" (Some et al., 2016). One argument against the use of this measure is that the variance in "fatness" is not taken into account. For example, a muscular individual may be classified as "obese". A further implication is that ethnicity is not taken into account when using the standard obesity threshold. Widespread research confirms that ethnicity and population group differences result in varied optimal obesity cut-off points (National Institute for Health and Clinical Excellence, 2013).

In an attempt to define ethnic specific obesity cutoffs for diabetes risk, academics in Glasgow examined data on more than 490 000 participants of the UK Biobank. Since diabetes is strongly correlated with obesity, these measures are used as thresholds (Table 1). Since the race group "Coloured" has no classification, the guideline measure of 30kg/m2 is used.

This paper addresses the issues highlighted in the literature survey by using ethnicity-specific obesity thresholds as given by Ntuk et al. (2014) to capture the impact of obesity in labour market outcomes as well as to fill a vacuum in the literature by quantifying the discrimination of obese persons while taking endogeneity into account. This method of measuring wage discrimination due to obesity has not been applied in a South African context. Literature has used this method to provide evidence that there is a wage-gap between genders (Oaxaca, 1973) or that there are racial disparities between obese and non-obese persons (Sen, 2014), however the two have not been married.

3 THEORETICAL DETERMINANTS

Theory indicates that the relationship between BMI and employment status is that increases in BMI will increase the probability of an individual getting employed (as an individual becomes healthier) but these increases in BMI will eventually lead to a decrease in the probability of employment as the individual tends to become overweight and obese, leading to employer prejudice or a perceived lack of productive ability (Morris, 2007 & Some et al., 2016). Hence, the need to consider the non-linear relationship between BMI and labour market outcomes. According to Dasgupta and Ray (1986), increased food consumption of possibly underweight/malnourished individuals increase their work capacity at an increasing rate. However, this is followed by diminishing returns and ultimately negative returns as consumption increases and the individual's BMI continues to grow. The natural limits imposed by the human body restrict the conversion of additional nutrition into a forever increasing work capacity. It thus follows that obesity restricts working capacity.

The inclusion of the other chosen covariates is supported by the literature: Some et al. (2016), Harkonen et al. (2011), Morris (2007) and Cawley, Grabka & Lillard (2005). Their hypothesised coefficient signs are discussed below.

Age and its square (age2) are widely used in labour market related literature. It is expected that increases in age will increase employment probability and wages up until a certain point where this relationship turns negative. This is because older individuals may be less attractive to employers. Additionally, the level of education is a general determinant. The higher ones' education, the higher their associated productivity and skill. The expectation is that more educated individuals are more likely to become employed and earn a higher wage.

Gender based labour market discrimination is widely accepted as a reality in the South African labour markets (Kollamparambil and Razak, 2016). It is expected that females are less likely to be employed due to discrimination and more likely to earn lower wages. It is further expected that obese females will have greater negative coefficients compared to males, and therefore face discrimination (Cawley, 2004; Morris, 2007; Johansson et al., 2009; Lindeboom et al., 2010 & Some et al.,2016).

The inclusion of family orientated variables such as marital status, household size and household income is warranted because married individuals are more likely to put greater effort into finding a job (maintaining a job) therefore increasing their probability of employment (wages). All income has been adjusted for inflation.

Self-perceived health status is included, it is expected that those that rate themselves as less healthy are less likely to get employed and more likely to earn lower wages. Based on Harkonen et al. (2011), this variable is assumed to have significant predictive power.

Further, the geography-type of individuals are included. It is expected that those that live in urban areas are more likely to get employed and earn higher wages, this is due to the distant nature of rural areas and the concentration of job availability in urban areas (Baum & Ford, 2004; Villar, Oreffice & Quintana-Domeque, 2011).

4 DATA & DESCRIPTIVE STATISTICS

4.1 Data & Variables

The data used in this analysis comes from the National Income Dynamics Survey (NIDS) which is administrated by the Southern Africa Labour and Development Research Unit (SALDRU). It is the first national panel study in South Africa encompassing over 28000 individuals in approximately 7300 households. All four waves of the data will be used dating from 2008-2015. Panel weights are assigned to observations to take into account attrition bias and survey design bias.

The sample size excluding pregnant women, self-employed, economically inactive, not of working age (beyond the bounds of 15-65 years) and with missing data is 4243 individuals per wave. Data for nonresponse on weight and height has a small effect as BMI appears to approximate a normal distribution (appendix A). For the purpose of this study, BMI is calculated in line with the WHO standard for obesity measurement, as the person's weight in kilograms divided by the square of height in meters based on NIDS data. An obese individual is identified based on race specific thresholds given in Table 1.

The covariates used are as discussed in the theoretical determinants section which include: age (Age), BMI (BMI), gender (Gender), race (White is taken as the benchmark and other categories included are African, Coloured, Indian/Asian), household size (hhsize), log of household income (lnhhincome), self-perceived level of health (perchealth), urban (urban), education in years (eduyears) and marital status (Marital Status), of which their expected coefficients have been discussed. Self-perceived level of health range from 1 to 5, where 1 is excellent and 5 is poor. Urban takes on the value 1 if the respondent lives in an urban area and 0 if the respondent lives in a rural area, these classifications were taken from the 2011 General Census Survey. Gender is a dummy variable, 1 if the respondent is a male and 0 if the respondent is a female. The dependent variables are employment status (employdummy taking the value 1 if employed and 0 otherwise) and log of wage levels (lnfwag).

4.2 Descriptive Statistics

Table 2 shows that on average females tend to have a higher average BMI than males. Females in particular, generally exhibit an upward trend in BMI over time. On average White individuals tend to have a larger BMI than individuals from other race groups and Coloured females seem to have the largest average BMI overall.

It is evident from Table 3 that overtime, the age groups 20-24, 30-34 & 40-44 have had consistent increases in their BMI compared to the other age groups. One expects the majority of the labour force to lie within these age groups. A definite increase in all BMI's from Wave 1 to 4 is noticed except for older individuals in recent waves.

Table 4 shows that the proportion of obese has been increasing over time.

In Wave 1, 33.6% of the sample were obese, this increased to 45.1% in Wave 4. Additionally, the employment rate of obese persons has experienced mainly upward trends over time. This relation could be explained due to the simultaneity mentioned above, i.e. that employment may cause obesity and underlines the need to take endogeneity into account in regression estimations.

Lastly, the means of all variables used are shown in Table 5. The average log of wages, BMI, education in years, age and the average log of household income all show increasing trends overtime. On average, South Africans appear to rate themselves as being marginally healthier in more recent periods. The racial composition of the sample has been adjusted using the weight variables provided with NIDS. The use of the weights has improved the sample composition to more accurately reflect these proportions. Within these groups, the sample shows a declining proportion of males, from 57% in Wave1 to 52.2% in Wave 4, these estimates are on par with Statistics South Africa estimates (Statistics South Africa, 2014). The average household size remains at around 4 individuals throughout the panel, while the proportion of married individuals decreased by around 3%. In recent periods, the proportion of individuals who are engaged in casual work has significantly decreased whereas the proportion of individuals that are employed has increased by 13% from Wave 1 to Wave 4.

5 METHODOLOGY

The benchmark models employed are ordinary least Squares regressions to estimate the impact of obesity on the employment probability and wage determination. These liner estimations treat the relationship between BMI on the one hand and the probability of employment as well as wage levels on the other hand, as exogenous. Next we use non-linear estimations using probit and tobit regressions, retaining the assumption of exogeneity but accounting for the panel nature of dataset. Progress is made to a dynamic GMM to account for endogeneity and reduce specification bias by including the autoregressive term. Further, the quantification of discrimination against the obese is undertaken using the Blinder-Oaxaca (1973) decomposition. Lastly, the decomposition analysis is extended to gender specific analysis of obesity-related discrimination.

Probit model:

This model estimates the probability of the respondents' employment status. This model assumes that obesity is independent of employment. Thus, there is no endogeneity. The dependent variable Employed is the respondent's employment status. The broad measure of unemployment was used to create the variable. A value of 1 indicates that the individual is employed, and 0 if otherwise. Probability of employment will be based on the following equations (Wooldridge, 2002):

$$Employed*_{it} = \alpha + \beta BMI_{it} + \eta X_{it} + \varepsilon_I \tag{1}$$

$$\left\{\begin{matrix} Employed = 1 \ if \ Employed_i^* > 0 \\ Employed = 1 \ if \ Employed_i^* \leq 0 \end{matrix}\right\} \tag{2}$$

Where, BMI is the respondents respective BMI and X is a set of factors affecting employment. All covariates were mentioned in Section 3.

The probability that an individual is employed is calculated using integral calculus where Φ is the normal density function (Wooldridge, 2002).

$$\Pr ob \ (Employed = 1 \ |x = \int_0^{x'\beta} \Phi(t)dt = \Phi(x'\beta) \tag{3}$$

The marginal effects for both probit models is done relative to the sample means of the other regressors. The average marginal effect is thus computed as (Some et al., 2016):

$$Average \ M \arg inal \ Effect = \frac{\Phi(\hat{\alpha} + \hat{\beta} + \hat{\eta}\bar{X}) - \Phi((\hat{\alpha} + \hat{\eta}\bar{X})}{\Phi(\hat{\alpha} + \hat{\eta}\bar{X})} \tag{4}$$

Tobit model:

The dependent variable is the log of wages. Those without wages are allocated the value zero and given the limited dependant variable we consider the tobit regression as appropriate. The independent regressors (Xi) are similar to those above lsep

$$LnWages_{it} = X_{it}\beta_j + u_i + \varepsilon_{it} \tag{5}$$

where i is the individual and t is the time, $t = 1, 2, 3, 4$. u_i captures the unobservable effect of time-invariant factors and ε_{it} captures the stochastic disturbances of the model.

A dynamic system GMM:

A dynamic system GMM that determines the effect of obesity on employment status and wages that take endogeneity into account follows. This model is an augmentation of Arellano and Bover (1995) that was fully modelled by Blundell and Bond (1998) (Roodman, 2009). The model is treated as a system of equations by their respective time period which differ in their instrument variable compilation. Lags and strictly exogenous variables are used to instrument predetermined and endogenous variables which are placed in an internal instrument matrix (Roodman, 2009). The advantage of using dynamic GMM lies in incorporating autoregressive variables as well as to counter autocorrelation and specification bias. Moreover, endogeneity issues are better tackled using internal variables in lagged form as instruments. The two step system GMM estimation method is used to ensure that the estimators are asymptotically more efficient.

$$Y_{it} = \beta x_{it} + \eta w_{it} + \varepsilon_{it} \tag{6}$$

$$\varepsilon_{it} = \propto_i + \nu_{it} \tag{7}$$

Where Y_{it} is employment status, thereafter a second regression is run where Y_{it} is the log of wages, x_{it} is a vector of strictly exogenous covariates such as age, age2, African, Coloured, Indian, time dummy variables (wave 1 wave2 wave3) gender and the lags of other covariates such as household size and income, geotype and education in years. w_{it} is a vector of predetermined covariates, which include the lag of employment status and endogenous covariates which may be correlated with past and present errors, i.e. BMI. $\propto_i$are unobserved group-level effects and ν_{it} is the observation-specific error term. The guidelines suggested by Roodman (2009) are adhered to, all Dynamic GMM models are run using the *xtabond*2 command in Stata14.

Blinder-Oaxaca decomposition

This study isolates the discrimination component of the gap between obese and non-obese persons using the Oaxaca-blinder approach. Oaxaca (1973) and Blinder (1973) introduced a decomposition procedure that enabled the attribution of the wage gap of two groups of people to labour market discrimination and differences in average characteristics between the groups, enabling researchers to identify the exact portion of wage gap that is not due to differences in average characteristics between the groups, and thus attributable to discrimination between the groups (Kollamparambil & Razak, 2015).

$$Y_{it}^{obese} = \alpha_i^{obese} + \beta^{obese} x_{it} + \varepsilon_{it}^{obese} \tag{8}$$

$$Y_{it}^{not\ obese} = \alpha_i^{not\ obese} + \beta^{not\ obese} x_{it} + \varepsilon_{it}^{not\ obese} \tag{9}$$

Where Y is the dependent variable and x is a vector of regressors similar to those mentioned above, however with the inclusion of the first lag of the dependent variable.

The decomposition is calculated by subtracting the two equations which yields:

$$\begin{gathered} Y_{it}^{non-obese} - Y_{it}^{obese} = \beta^{non\text{-}obese}(X_{it}^{non\text{-}obese} - X^{obese}) + \\ (\alpha_i^{non-obese} - \alpha_i^{obese}) + (\beta^{non-obese} - \beta^{obese})X^{obese} \end{gathered} \tag{10}$$

From equation 10, $\beta^{not\ obese}(X_{it}^{not\text{-}obese} - X^{obese})$ is the "explained" portion (a), of the gap. It is the wage-gap attributable to the differences in mean observable characteristics between non-obese and obese. $(\alpha_i^{non-obese} - \alpha_i^{obese})$ + $(\beta^{not-obese} - \beta^{obese})X^{obese}$ is the "unexplained" portion (b + c), i.e. the differences in constant and coefficient estimates. This is the obesity disparity in wages that would still remain if obese persons had the average characteristics of non-obese persons, i.e. the discrimination/unequal treatment. The total gap between non-obese and obese persons is the sum of the explained portion and unexplained portion. The limitation of this approach is that this gap, may also be a result of omitted variables/unobserved influences or measurement errors. Nevertheless, using the dynamic GMM regression with autoregressive term is expected to minimize the bias.

This paper estimates the discrimination using a probit model where the dependent variable is employment status and a tobit model where the dependent variable is the log of wages in the determination of the exogenously treated discrimination effect. These estimates of discrimination are then compared to the estimates of discrimination using the system GMM regressions that account for endogeneity.

6 MULTIVARIATE REGRESSION RESULTS

6.1 Employment Probability

Results show that BMI and BMI2 are significant at the 1% level of significance but of opposite signs, indicating the non-linear relationship between BMI and employment probability in all three estimations (Table 6). Marginal effects of OLS and logit regressions are very close indicating that a unit increase in BMI leads to 3% and 2.8% increase in the probability of being employed up until a certain point. Increased BMI beyond the point leads to a 0.04% decrease in the probability of being employed based on both the models.

Dynamic GMM analysis proves that the former relation exhibited in the probit model still hold once endogeneity is taken into account. The coefficient of BMI is positive whereas the coefficient of BMI2 is negative indicating an inverted U-shaped relationship between BMI and employment probability. A unit increase in BMI leads to an increase in the probability of being employed by 5.7% up until a point where this relationship turns negative leading to a 0.1% decrease in probability of being employed. It is clear that although the significance level is now only at 10%, the level of impact has in fact increased upon considering endogenieity. Lagged employment status positively affects the probability of employment and is significant at the 1% level, indicating the relevance of an auto-regressive model. Years of education and being male positively impact employment probability. Casual is positive and significant at a 10% level indicating that casual employment contributes to the probability of being employed. The validity of the instruments is implied by the highly insignificant Hansen and Difference test p-values.

6.2 Wages

Results from the OLS, tobit and dynamic GMM models (Table 7) are consistent across models in highlighting the inverted U-shaped non-linear relationship between BMI and wages. While initial increases in BMI contributes to higher wages, this relationship turns negative at higher levels of BMI. Comparing the two linear estimates, it may be highlighted that the coefficient of BMI from the dynamic GMM that take endogeneity into account is higher than the OLS estimates indicating that the impact of BMI is underestimated while ignoring endogeneity. However, just as in the case of employment probability, taking endogeneity into account in wage level estimations makes the results statistically significant only at 10%. According to the system GMM results, a one unit increase in BMI leads to a 31% increase in wage levels initially, however beyond the optimal BMI the wage levels decrease by 0.6% for every unit increase in BMI. This is higher than the tobit estimates of 26% and -0.4% for BMI and BMI2 respectively. The Hansen and Difference in Hansen tests were insignificant, supporting the validity of the instruments.

The dynamic GMM results further indicate that middle aged, unmarried individuals, males, individuals from higher household incomes, individuals with more years of education, residents of urban areas are seen to earn higher wages. Households that are larger in size and individuals who rate themselves as less healthy tend to earn a lower wage.

Having established the relationship between BMI and employment probability/ wages we next turn to quantifying the obesity related discrimination. This warrants the need for the Blinder-Oaxaca decomposition to investigate the discrimination against obese individuals.

7 RESULTS: BLINDER-OAXACA APPROACH TO MEASURING DISCRIMINATION

7.1 Overall Discrimination

Table 8 shows the decomposition of employment-status-discrimination between obese and non-obese persons using the regressions shown in appendix B. The analysis indicates that if obese individuals had the same characteristics as non-obese individuals, their average probability of employment would increase by 4%. The explained portion of the gap in employment status accounts for 126.5%. The differences in coefficients account for 77.3% of the gap, meaning that the probability of employment when non-obese coefficients are applied to obese will increase by 2.5%. The simultaneous effect of differences in endowments and coefficients are negative. The sum of the latter two components is attributable to the discrimination. Thus, the discrimination that obese individuals face in the labour market without taking endogeneity into account is -26.5% of the employment status-gap. This shows that obese persons are generally preferred to non-obese. When endogeneity is taken into account the Oaxaca decomposition results show that if obese individuals had the same characteristics as non-obese individuals the probability of an obese person becoming employed would increase on average by 9%. The differences in coefficients account for -322% of the gap. The total discrimination faced by obese persons in the probability of being employed as measured by the unexplained portion is 90%.

The wage-gap that shows the discrimination effects of individuals that are employed are shown in Table 9. Treating the relationship as exogenous yields discrimination of around 27.59%. The explained portion of the wage-gap accounts for 72.4%. This is less than the explained portion of the employment-status-gap. The differences in coefficients account for 47.18%, indicating that the change in the log of wages when non-obese coefficients are applied to obese individuals will increase by 0.09. The simultaneous effect of differences in endowments and coefficients are negative. The Oaxaca decomposition when endogeneity is taken into account indicates that if obese individuals had the same characteristics as non-obese individuals the log of wages of an obese person would decrease on average by 0.2. The differences in coefficients account for negative 119%, indicating that the change in the log of wages when non-obese coefficients are applied to obese individuals will decrease by 0.3. This effect is much larger than that of the exogenous decomposition. Once individuals are employed the wage-gap between obese and non-obese due to discrimination accounts for 186%.

It is clear that endogeneity biased discrimination downwards and needs to taken into account in estimating discrimination. Our results show that once individuals are employed, discrimination of obese individuals is almost 7 times larger and fully accounts for the wage-gap when endogeneity is taken into account. Additionally, obese persons face more than double the discrimination once they are employed rather than when determining their employment status. In other words, the wages of obese persons are more discriminated against by their obesity status rather than whether they will be employed or not.

Due to the dominant female composition of the obese group, further discrimination is calculated within gender. The following results show the gender discrimination between non-obese and obese.

7.2 Discrimination of obese persons by Gender

Having established the need to take into account endogeniety, all gender related Blinder-Oaxaca decompositions are determined using system GMM regressions that take endogeneity into account. The calculations underlying the decomposition can be found in Appendix C. Table 10 shows that the differences in coefficients fully account for the employment-status gap. The total discrimination faced by obese females in the probability of being employed is 109%. On the other hand, 284% of the employment-status-gap is explained for males whereas the total unexplained portion due to discrimination that obese males face is negative 184%. Therefore, obesity matters for females but not for males in the determination of employment status. These results are on par with expectations formed by literature review.

Table 10: Employment Status Discrimination of Obese Persons By Gender

Among employed individuals, the discrimination that females experience is still higher than that of males (Table 11). If obese females had the same characteristics as non-obese females the log of their wages would decrease by 0.07, the explained portion of the gap accounts for 27%. The unexplained portion due to discrimination accounts for 73% of the wage gap. It is shown that if obese males had the same characteristics as non-obese males the log of their wages would decrease by 0.2, this is a larger negative effect than that for females. The total explained portion accounts for 65% of the wag-gap between obese and non-obese males. The magnitude of the gap is 35%, attributable to discrimination between non-obese and obese males, half of the discrimination faced by females. These findings correspond to those of Dackleburg et al. (2014).

Thus, obese males face negative discrimination in whether they enter the labour market or not, whereas obese females face positive and greater discrimination. However, once individuals are employed, obese females double the discrimination that obese males do in the determination of wages.

8 CONCLUSIONS

In summary, the relationship between BMI and employment probability /wages are seen to be non-linear with increases in BMI leading to an increase in the probability of employment and wages up until a threshold beyond which this relationship becomes negative. These results are consistent across models that don't take endogeneity into account and those that do. However the relationship is seen to be stronger in estimations that have accounted for endogeneity.

The main contribution of this paper is to measure the extent of discrimination taking into account ethnicity-based obesity thresholds. Although the relationship between BMI and the labour market outcomes yield consistent estimates between exogenous and endogenous results, exogenous models seem to underestimate obesity related discrimination. Blinder-Oaxaca estimates that take endogeneity into account have shown that 90% of the gap in employment status is accounted for by obesity related discrimination. With regards to wages, obesity leads to a discrimination of 186%. When disaggregating this discrimination further, by gender, it was found that obese females face discrimination in entering the labour market of 109% compared to a negative discrimination of -184% for obese males. In determining wages, employed obese females face discrimination of around 73% whereas the discrimination endured by employed obese males is half of this, at 35%. Our findings thus reiterate that obesity related discrimination exists and is predominantly faced by obese South African women entering the workplace and continues in their wage determination.

The study findings support the need for fiscal policy interventions as well as an awareness drive to reduce obesity in South Africa bearing in mind not just its health-related costs but also its labour market implications. Further labour market policy interventions need to be informed by whether the observed discrimination is due to employer prejudice-perhaps through qualitative studies on employer preferences- or due to the decrease in productivity as a result of the disease. Further research breaking down discrimination by various professions/sectors across various ethnicities is called for. The need for this research is imperative to understanding this form of social discrimination and finding solutions that induce a healthier labour force and more equitable labour market outcomes.

References

[1] Adeboye, B., Bermano, G.,& Rolland, C. (2012). Obesity and its health impact in Africa: A systematic view, Cardiovascular Journal of Africa, 23(9): 512–521.

[2] Asgeirsdottir, T. L. (2011). Obesity & Employment: The case of Iceland. University of Iceland, Department of Economics

[3] Barnett, A., Kumar, S. (2009). Obesity & Diabetes, Second Edition. Southern Gate, United Kingdom: John-Wiley & Sons.

[4] Baum, C., & Ford, W. (2004). The wage effects of obesity: a longitudinal study. Health Economics, 13 (9), 885-99.

[5] Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. Journal of Human Resources 8: 436-455.

[6] Cawley, J. (2004). The Impact of Obesity on Wages. The Journal of Human Resources, 39 (2), 451-474.?

[7] Cawley J, Han E, Norton EC. (2009). Obesity and labor market outcomes among legal immigrants to the United States from developing countries. Economics & Human Biology, July 7(2):153-64.

[8] Department of Health. (2015). Strategy for the Prevention & Control of Obesity in South Africa 2015-2020. Department of Health: Republic of South Africa.

[9] Dackleburg, M., Gerdtham, U.G., & Nordin, M. (2014). Productivity or discrimination? An economic analysis of excess-weight penalty in the Swedish labor market. The European Journal of Health Economics, 16 (6), 589-601.

[10] Dasgupta, P., & Ray, D. (1986). Inequality as a Determinant of Malnutrition and Unemployment: Theory. The Economic Journal, 96 (384), 1011-1034.

[11] Daymont, T. N., and P. J. Andrisani. (1984). Job preferences, college major, and the gender gap in earnings. Journal of Human Resources 19: 408-428.

[12] Fairbrother K. A (2009). Healthcare burden of obesity in South Africa: A reflection on the role of government, University of Witwatersrand, Johannesburg. Accessed at: http://wiredspace.wits.ac.za/bitstream/handle/10539/8792/ AmyFairbrother_ResearchReport_FinalSubmission.pdf?sequence=1

[13] Garcia, J. & Quintana-Domeque, C. (2006). Obesity, Employment, and Wages in Europe. Advances in Health Economics and Health Services Research 17.

[14] Greve J. (2008). Obesity and labor market outcomes in Denmark. Economics and Human Biology. Dec;6(3):350-62.

[15] Harkonen, J., Rasanen, P., & Nasi, M. (2011). Obesity, Unemployment, and Earnings. Nordic Journal of working life studies, 1 (2), 23-38.

[16] Harper, B. (2000). Beauty, stature and the labour market: A British cohort study. Oxford Bulletin of Economics and Statistics, 62, 771-801.

[17] Jann, B. (2008). A Stata implementation of the Blinder-Oaxaca decomposition Ben Jann. The Stata Journal, 8 (4), 453-457

[18] Johansson E, Böckerman P, Kiiskinen U, Heliövaara M. (2009). Obesity and labour market success in Finland: the difference between having a high BMI and being fat. Economics and Human Biology. Mar;7(1):36-45.

[19] Kollamparambil, U., & Razak, A. (2016). Trends in Gender Wage Gap and Discrimination in South Africa: A Comparative Analysis across Races. Indian Journal of Human Development, 10 (1), 5-9.

[20] Lindeboom M, Lundborg P, van der Klaauw B.(2010). Assessing the impact of obesity on labor market outcomes. Economics and Human Biology. 8(3):309-19.

[21] Malan, M. (2014, May 29). SA is the fattest sub-Saharan African nation - study. Retrieved from Bhekisisa Centre for Health Journalism: http://bhekisisa.org/article/2014-05-29-00-sa-has-the-fattest-sub-saharan-african-nation-study [Accessed: 12 August 2016].

[22] Mcpherson, M. A., Redfearn, M. R., & Tieslau, M. A. (2006, August 23). A Re-Examination of the Linder Hypothesis: A Random-Effects Tobit Approach. International Economic Journal, 127-129.

[23] Morris, S. (2007). The Impact of Obesity on Employment. Labour Economics, 14 (3), 413-433.

[24] National Institute for Health and Clinical Excellence (NICE). (2013). Assessing body mass index and waist circumference thresholds ethnic groups in the UK (PH 46) [Online]. Available from: http://www.thehealthwell.info/node/522752 [Accessed: 1th May 2016].

[25] National treasury (2016). Taxation of sugar sweetened beverages, Economics tax analysis chief Directorate policy paper, Government of South Africa, Pretoria.

[26] Ng, M., Fleming, T., Robinson, M., Thomson, B., & Graetz, N., et al. (2014). Global, regional, and national prevalence of overweight and obesity in children and adults during 1980–2013: A Systematic Analysis for the Global Burden of Disease Study 2013. The Lancet, 384 (9945), 766-781.

[27] Ntuk, U., Gill, J., Mackay, D., Sattar, N., & Pell, J. (2014). Ethnic-specific obesity cutoffs for diabetes risk: cross-sectional study of 490,288 UK Biobank Participants. Diabetes Care, 37 (9), 2500-7.

[28] Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. International Economic Review. 14: 693-709.

[29] Oaxaca, R. L., and M. R. Ransom. (1994). On discrimination and the decomposition of wage differentials. Journal of Econometrics 61: 5-21.

[30] Pinkston, J. C. (2015). The Dynamic Effects of Obesity on the Wages of Young Workers. University of Louisville, Department of Economics. University of Louisville.

[31] Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal, 9 (1), 86-136.

[32] Sargent, J., & Blanchflower, D. (1994). Obesity and stature in Adolescence and earnings in young adulthood. Analysis of a British birth cohort. Archives of Pediatrics and Adolescent Medicine 148, 681–687. 147 (7), 681-7.

[33] Sarlio-Lahteenkorva, & S., E. Lahelma (1999). The association of body mass index with social and economic disadvantage in women and men. International Journal of Epidemiology, 28, pp.445-449.

[34] Sen, B. (2014). Using the Oaxaca–Blinder Decomposition as an Empirical Tool to Analyze Racial Disparities in Obesity. Obesity, 22(7), 170-1755.

[35] Some, M., Rashied, N., & Ohonba, A. (2016). The Impact of Obesity on Employment in South Africa. Studies in Economics and Econometrics, Volume 40, Issue 2, p. 87 – 104.

[36] Statistics South Africa. (2014). Mid-year population estimates 2014. Pretoria: Statistics South Africa.

[37] Tugendhaft, A., & Hofman, K. (2014). Empowering healthy food and beverage choices in the workplace. Occupational Health Southern Africa, 20 (5).

[38] Villar, J. G., Oreffice, S., & Quintana-Domeque, C. (2011). Physical Activity and Obesity in Spain: Evidence from the Spanish National Health Survey. The Economics of Sport, Health and Happiness: The Promotion of Well-being Through Sporting Activities.

[39] Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge (MA.).

[40] Wittenberg, M. (2011). The Weight of Success: The Body Mass Index and Economic Well-being in South Africa. School of Economics, SALDRU and DataFirst University of Cape Town.

Table 1: Ethnicity Specific Obesity Cutoffs

RACE	BMI
White	30
South Asians (Indian & Pakistani)	22
Black	26
Chinese	25

Source: (Ntuk, Gill, Mackay, Sattar, & Pell, 2014)

Table 2: Average BMI By Race & Gender Overtim

	WAVE 1		WAVE 2		WAVE 3		WAVE 4		TOTAL	
	MALE	FEMALE	MALE	FEMALE	MALE	FEMALE	MALE	FEMALE	MALE	FEMALE
AFRICAN	22.63	26.42	23.56	27.45	23.91	27.72	23.7	28.47	**23.45**	**27.51**
	(.11)	(.12)	(.11)	(.114)	(.11)	(.11)	(.11)	(.11)		
COLOURED	23.52	27.2	24.17	28.02	24.35	28.6	24.11	29.6	**24.04**	**28.36**
	(.37)	(.33)	(.38)	(.33)	(.36)	(.32)	(.39)	(.34)		
INDIAN	23.65	25.89	24.12	26.7	25.79	26.66	24.78	27.44	**24.59**	**26.67**
	(1.26)	(0.87)	(1.28)	(.96)	(1.3)	(.79)	(1.18)	(.96)		
WHITE	26.82	27.6	26.76	26.8	28.5	28.72	29.24	28,67	**27.83**	**27.94**
	(1.19)	(.93)	(1.06)	(.93)	(.78)	(.91)	(1.11)	(.85)		

*Standard deviations in parentheses ().

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.

Source: Author’s own calculations

Table 3: Average BMI By Age Interval (%)

AGE INTERVAL	WAVE 1	WAVE 2	WAVE 3	WAVE 4
15-19	21.53	22.94	22.56	.
20-24	**23.07**	**23.30**	**23.91**	**23.93**
25-29	24.34	24.51	24.69	24.51
30-34	**25.01**	**25.48**	**25.68**	**26.06**
35-39	26.50	26.51	26.83	26.55
40-44	**26.22**	**27.03**	**27.48**	**27.71**
45-49	26.87	26.96	26.49	27.02
50-54	27.69	27.78	28.53	27.24
55-59	27.04	28.75	28.18	28.11
60-65	.	26.19	28.11	27.41

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
Source: Author's own calculations

Table 4: Proportion of Obese By Employment Status (%)

	WAVE 1	WAVE 2	WAVE 3	WAVE 4
OBESE	**33.6**	**39.66**	**42.85**	**45.1**
Employed	46.35	38.73	46.28	51.58
Unemployed	53.65	61.27	53.72	48.42
NOT OBESE	**66.4**	**60.35**	**57.16**	**54.5**
Employed	36.93	37.65	43.82	53.69
Unemployed	63.07	62.35	56.18	46.31

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition
Source: Author's own calculations

Table 5: Variable Means

)	WAVE 1	WAVE 2	WAVE 3	WAVE 4
Wages (log)	7.55 **	7.68**	7.78**	7.87**
Employed	0.4**	0.38**	0.45**	0.53**
Casual	.014 **	.005 *	.001*	. 007**
BMI	25.96 **	26.192**	26.431**	26.585**
BMI2	698.621 **	713.1 **	726.106 **	736.805**
Married	.402**	.399**	.362**	.375**
African	0.817**	0.826**	0.868**	0.874**
Colored	0.112**	0.096**	0.073**	0.061**
Indian/Asian	0.025**	0.028**	0.021**	0.025**
White	0.047**	0.051**	0.038**	0.041**
Male	.57**	.549**	.561**	.522**
Age	37.191**	38.835**	38.776**	39.118**
Age2	1583.184**	1615.226**	1619.466 **	1649.434**
Education (years)	9.652 **	9.843 **	9.865 **	10.237**
Household income	7.89 **	8.014**	8.16 **	8.34**
Household size	3.884 **	4.044 **	3.998 **	4.068**
Perceived health	2.123 **	1.848**	2.04 **	1.99**

**p<0.01 *p<0.05

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Author's own calculations

Table 6: Regression results- Employment Status

	LPM	Probit (Marginal Effects)	System GMM (2 step)
Lag Dep Variable		-	0.201*** (0.0407)
BMI	.0297*** (.0056)	.0277*** (.0101)	0.057* (0.0339)
BMI2	-.0004*** (.0001)	-.0004** (.0002)	- 0.001* (0.006)
Age	.0898*** (.0075)	.1833*** (.0147)	0.014 (0.0319)
Age2	-.0014*** (.0002)	-.0033*** (.0039)	0.000 (0.0007)
African	.0648* (.0379)	.1369 (0.0833)	0.126 (0.0922)
Colored	.1500*** (.0389)	.2714 *** (.0855)	0.068 (0.1019)
Indian	-.0555 (.0516)	-.1072 (.1139)	-0.119 (0.1582)
Male	.1581*** (.0075)	.262*** (.0168)	0.109 *** (0.0344)
Urban	.0398 (.0078)	.0261 (.0163)	0.011 (.1817)
Married	-.0205*** (.0091)	-.0433 *** (.0178)	-0.0377 (.0414)
Household size	-.0202*** (.0011)	-.0349*** (.0021)	-0.0293* (0.0164)
Household income	.0000*** (.0000)	.0000 *** (.0000)	0.144* (0.0785)
Education	.0104*** (.0011)	.0139*** (.0024)	0.013** (0.0055)
Perceived health	-.0200*** (.0034)	-.0014 (.0051)	0.142 (0.1552)
Casual	.5934*** (.0151)		.652* (0.3534)
Constant	-1.314*** (.0882)	-	-2.388 ** (1.1086)
N	16972	16,972	8486
Groups		4243	4243
Wald Chi2(15)		1680.79	
R sq	.183		

Exogeneity of instruments			Hansen test: Prob > chi2 = 0.965 Difference: Prob > chi2 = 0.996

*** p<0.01; ** p<0.05; * p<0.1
Notes: Standard errors in Parentheses. All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
GMM Instruments: L2.bmi2 L2.lnhhincomereal L2.marrieddummy L2.eduyears L2.casual
L2.hhsize age age2 age3 african coloured indian gender wave1 wave2 wave3 L2.heartdummy L2.bloodpdummy
Source: Authors' own estimation

Table 7: Regression results- Wages

	OLS	Tobit	Dynamic GMM
L.lnfwag	-	-	-.0891* (.0489)
BMI	.2600*** (.0433)	.4281*** (.139)	.3132* (.1689)
BMI2	-.0040*** (.0008)	-.0059** (.0025)	-.006 * (.0029)
Age	.4408*** (.0128)	1.736*** (.057)	.067 *** (.1882)
Age2	-.0051 (.0001)	-.0204*** (.0007)	-.0001*** (.0002)
African	.0278 (.2761)	.2054 (1.140)	.1597 (.1439)
Colored	.5851** (.2835)	2.222** (1.182)	.5149 (.1689)
Indian	-.7167* (.3758)	-1.582 (1.127)	-.4297*** (.1492)
Male	1.279*** (.0576)	3.1963*** (.2250)	.3046*** (.0618)
Urban	.4614*** (.0572)	1.089*** (.2246)	.0920 * (.5305)
Married	.0158 (.0658)	-.7855 *** (.2291)	-.1128 *** (.0584)
Household size	-.1586*** (.0080)	-.4548*** (.0294)	-.1294 *** (.0269)
Household income	.0000*** (.0000)	.0000*** (.0000)	1.027 *** (.0863)
Education	.148 (.0085)	.5522*** (.0364)	.028 ** (.0129)
Perceived health	-.2436*** (.0253)	-.2140*** (.0671)	-.0847 (.0693)
Constant	-10.715*** (.6726)	-47.32*** (2.465)	-5.7155** (2.5269)
N	5136	15,972	1580
Groups		4243	790
Adj-R2	0.224		
F	331.6***		
Wald chi2(16)		722413.4***	
Exogeneity of instruments			Hansen test: Prob > chi2 = 0.415

			Difference: Prob > chi2 = 0.616

*** p<0.01; ** p<0.05; * p<0.1
Notes: Standard errors in Parentheses. All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
GMM Instruments: L2.marrieddummy L2.eduyears L2.urban L2.casual ivhead L2.eduyears age age2 african coloured indian gender wave1 wave2 wave3
Source: Authors’ own estimation

Table 8: Blinder-Oaxaca Discrimination: Employment Status

	PROBIT (EXOGENOUS)		DYNAMIC GMM	
	Coefficient	**Percentage**	**Coefficient**	**Percentage**
Explained portion (a)	. 0403	127%	0.8952	10%
Difference in Coefficients (b)	.0246	77%	3.0079	322%
Differences in constant (c)	-.0331	-104%	-2.1640	-232%
Total	.0319	100%	0.9334	100%
Discrimination (d)= b+c		**-26.5%**		**90%**

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
GMM Instruments: L2.casual L2.perchealth L2.lnhhincomereal L2.eduyears age age2 african coloured indian gender wave1 wave2 wave3 ivhead
Source: Author's own calculations

TABLE 9: Blinder-Oaxaca Discrimination (Using System Gmm)

	TOBIT (EXOGENOUS)		DYNAMIC GMM	
	Coefficient	**Percentage**	**Coefficient**	**Percentage**
Explained portion (a)	.1371	72%	-0.2131	-86%
Difference in Coefficients (b)	.0893	47%	-0.2953	-119%
Differences in constant (c)	-.0371	-20%	0.7572	304%
Total	.1893	100%	0.2489	100%
Discrimination (d)= b+c		**27.59%**	0.4620	**186%**

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
GMM Instruments: age age2 african coloured indian wave1 wave2 wave3 ivhead gender L2.eduyears L2.hhsize L2.perchealth L2.lnhhincomereal L2.urban
Source: Author's own calculations

Table 10: Employment Status Discrimination of Obese Persons By Gender

	FEMALES		MALES	
	Coefficient	**Percentage**	**Coefficient**	**Percentage**
Explained portion (a)	0.0005	-9%	-0.636	284%
Difference in Coefficients (b)	-0.5922	11471%	3.067	-1368%
Differences in constant (c)	0.5866	-11362%	-2.655	1184%
Total	-0.0053	100%	-0.224	100%
Discrimination (d)= b+c	-0.0056	109%	0.412	-184%

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
GMM Instruments:
Females: L2.lnhhincomereal L2.marrieddummy L2.eduyears L2.urban L2.hhsize age age2 african coloured indian wave1 wave2 wave3
Males: L2.marrieddummy L2.urban L2.eduyears L2.casual age age2 african L2.perchealth coloured indian wave1 wave2 wave3
Source: Author’s own calculations

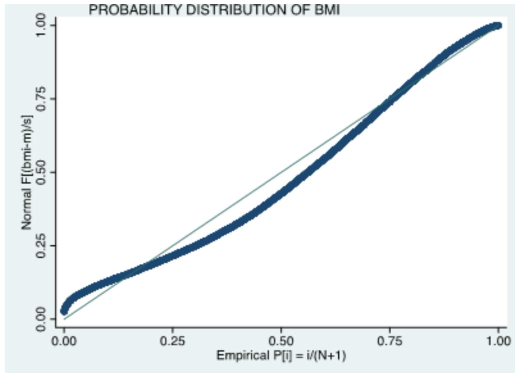
Table 11: Wage Discrimination of Obese Persons By Gender

	FEMALES		MALES	
	Coefficient	**Percentage**	**Coefficient**	**Percentage**
Explained portion (a)	-0.0691	27%	-0.1884	65%
Difference in Coefficients (b)	-4.3739	1686%	-1.7252	600%
Differences in constant (c)	4.1837	-1613%	1.626	-565%
Total	-0.2593	100%	-0.2877	100%
Discrimination (d) = b+c	-0.1902	73%	-0.0992	35%

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition.
GMM Instruments:
Females: L2.lnhhincomereal L2.hhsize L2.urban L2.eduyears L2.perchealth age age2 african coloured indian wave1 wave2 wave3 ivhead
Males: L2.marrieddummy L2.urban L2.eduyears L2.casual age age2 african L2.perchealth coloured indian wave1 wave2 wave3
Source: Author’s own calculations

APPENDIX

A: NORMAL STANDARDIZED DISTRIBUTION OF BMI



B: BLINDER OAXACA DECOMPOSITIONS
B1: EXOGENOUS BLINDER OAXACA

	Employment (Probit)		Wages (Tobit)	
	Obese	**Non-Obese**	**Obese**	**Non-Obese**
Education	.022***	-.013	.057***	.048***
Age	.291***	.463 ***	.069	.173***
Age2	-.005**	-.009***	-.001	-.004***
Gender	.679***	.452***	.391***	.226***
Married	-.377***	-.055	-.088**	.044
Urban	.085*	-.001	.036	.029
Perceived health	-.048**	-.087 ***	-.039**	-.044***
African	.828***	.695	-0.027	-.029
Coloured	.742***	.714***	-.0602	-.116
Indian	-.329	.542*	-0.087	-.181
Household size	-.092***	-.106***	-.075***	-.081***
Household income	.479***	.553***	.731***	.685***
Constant	-9.87 ***	-11.65***	-0.0214	-.745
N	**6646**	**10326**	**6646**	**10326**

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimation

B2: EMPLOYMENT STATUS (DYNAMIC GMM)

	βnon-obese	$\bar{X}_{non-obese}$	βobese	$\bar{X}_{obese}$	βnon-obese ($\bar{X}_{non-obese}$ $\bar{X}_{obese}$)	(βnon-obese - βnon-obese)$\bar{X}_{obese}$
L. employed	0.085*	0.410	0.224***	0.473	-0.005	-0.066
Casual	0.375	0.070	0.239	0.034		
Gender	0.078*	0.585	0.143**	0.286	0.023	-0.019
Age	0.096***	36.339	0.050***	41.89	-0.534	1.927
Age2	-0.001***	1477.8	-0.001***	1904.5	0.427	0.000
African	0.144	0.865	0.106	0.885	-0.003	0.034
Colored	0.281	0.078	0.075	0.053	0.007	0.011
Indian	-0.045	0.020	-0.215	0.041	0.001	0.007
Urban	-0.663**	0.549	-0.114	0.566	0.011	-0.311
Married	-0.467*	0.257	-0.072	0.465	0.097	-0.184
Household size	-0.061**	4.909	-0.027	5.103	0.012	-0.174
Household income	0.311***	8.310	0.128	8.541	-0.072	1.563
Education	0.019	9.270	0.009	9.214	0.001	0.092
Perceived health	-0.059	0.144	-0.126**	2.250	0.124	0.151
constant	-3.08***		1.444		0.000	
TOTAL					**0.0895**	**3.0079**
N	5163		3323			
Difference in constants	-2.164					
TESTS OF EXOGENEITY						
Hansen	Prob > chi2 = 0.171		Prob > chi2 = 0.348			
Difference	Prob > chi2 = 0.329		Prob > chi2 = 0.875			

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimation

B3: WAGES (DYNAMIC GMM)

	βnon-obese	$\bar{X}_{non-obese}$	βobese	$\bar{X}_{obese}$	βnon-obese $(\bar{X}_{non-obese} - \bar{X}_{obese})$	(βnon-obese - βnon-obese)$\bar{X}_{obese}$
L.Wages	0.007	7.927	-0.068	8.198	-0.002	0.607
Age	0.047**	40.40	0.057**	43.10	-0.125	-0.474
Age2	0.00	1722.36	-0.001*	1954.9	0.000	1.955
African	-0.142	0.818	0.11	0.882	0.010	-0.238
Colored	-0.277*	0.082	0.091	0.049	-0.009	-0.019
Indian	-0.395*	0.029	-0.183	0.033	0.002	-0.007
Urban	0.044	0.668	-0.066	0.728	-0.003	0.084
Married	-0.565***	0.435	-0.199	0.536	0.062	-0.216
Perceived health	-0.081	1.94	0.006	2.027	0.006	-0.150
Household size	-0.105***	3.774	-0.102***	4.181	0.042	-0.013
Household income	0.846***	8.771	0.93***	9.097	-0.227	-0.773
Education	0.041***	9.896	0.051***	10.24	-0.015	-0.092
Gender	0.326***	0.64	0.416***	0.474	0.054	-0.041
Wave1	0	0	0	0	0.000	0.000
Wave2	0	0	0	0	0.000	0.000
Wave3	0.018	0.452	0.015	0.465	0.000	0.001
Constant	-0.401		-1.169			
TOTAL					**-0.207**	**0.624**
N	946		634			
Difference in constants	0,75723					
TESTS OF EXOGENEITY						
Hansen	Prob > chi2 = 0.356		Prob > chi2 = 0.123			
Difference	Prob > chi2 = .586		Prob > chi2 = .312			

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimation

C1: FEMALE EMPLOYMENT STATUS (DYNAMIC GMM)

Females	βnon-obese	$\bar{X}_{non-obese}$	βobese	$\bar{X}_{obese}$	βnon-obese $(\bar{X}_{non-obese} - \bar{X}_{obese})$	(βnon-obese - βnon-obese)$\bar{X}_{obese}$
L.employed	0.214***	0.347	0.188***	0.373	-0.005	0.010
Casual	0.650	0.043	0.628***		0.028	0.000
Age	0.060***	37.223	0.054***	41.712	-0.270	0.247
Age2	-0.001***	1548.3	-0.001**	1890.2	0.232	-0.166
african	0.406***	0.795	0.256	0.882	-0.035	0.132
Colored	0.437***	0.104	0.149	0.057	0.021	0.016
Indian	0.204	0.038	-0.148	0.036	0.001	0.013
Urban	-0.032	0.546	-0.003	0.536	0.000	-0.015
Married	-0.196***	0.252	-0.192***	0.396	0.028	-0.002
Perceived health	-0.183**	2.226	-0.077	2.329	0.019	-0.245
Household size	-0.030**	5.333	-0.023**	5.280	-0.002	-0.038
Household income	0.146**	8.380	0.198***	8.474	-0.014	-0.443
Education	-0.002**	9.348	0.009	8.896	-0.001	-0.096
Wave1	0.000	0.000	0.000	0.000	0.000	0.000
Wave2	0.000	0.000	0.000	0.000	0.000	0.000
Wave3	-0.004	0.528	0.008	0.486	0.000	-0.006
constant	-1.852***		-2.438***			
TOTAL					**0.00**	**-0.592**
N	2014		2830			
Difference in constants	0.587					
TESTS OF EXOGENEITY						
Hansen	Prob > chi2 = 0.138		Prob > chi2 = 0.521			
Difference	Prob > chi2 = .546		Prob > chi2 = 0.685			

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimation

C2: MALE EMPLOYMENT STATUS (DYNAMIC GMM)

Males	βnon-obese	$\bar{X}_{non-obese}$	βobese	$\bar{X}_{obese}$	βnon-obese $(\bar{X}_{non-obese} - \bar{X}_{obese})$	(βnon-obese - βnon-obese)$\bar{X}_{obese}$
L.employed	0.213***	0.484	0.281***	0.700	-0.046	-0.048
Casual	0.507***	0.090	0.594***	0.037	0.027	-0.003
Age	0.073***	35.490	0.044***	42.418	-0.506	1.230
Age2	0.000***	1406.5	0.000**	1959.5	0.000	0.000
african	0.479**	0.908	0.414***	0.906	0.001	0.059
Colored	0.282	0.062	0.453**	0.027	0.010	-0.005
Indian	0.027	0.010	-0.009	0.040	-0.001	0.001
Urban	0.014	0.534	0.019	0.648	-0.002	-0.003
Married	-0.351**	0.254	0.023	0.521	0.094	-0.195
Perceived health	0.034	2.065	0.160	2.067	0.000	-0.260
Household size	0.025	4.251	-0.038	3.828	0.011	0.241
Household income	0.521***	8.262	0.284	8.712	-0.234	2.065
Education	-0.017	9.279	-0.014***	9.869	0.010	-0.030
Wave1	0.000	0.000	0.000	0.000	0.000	0.000
Wave2	0.000	0.000	0.000	0.000	0.000	0.000
Wave3	0.058*	0.507	0.029	0.499	0.000	0.014
constant	-5.73***		-3.082***			
TOTAL					**-0.636**	**3.067**
N	2326		2764			
Difference in constants	-2.655					
TESTS OF EXOGENEITY						
Hansen	Prob > chi2 = 0.367		Prob > chi2 = 0.251			
Difference	Prob > chi2 = .230		Prob > chi2 = .188			

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimation

C3: FEMALE WAGES (DYNAMIC GMM)

Females	βnon-obese	$\bar{X}_{non-obese}$	βobese	$\bar{X}_{obese}$	βnon-obese ($\bar{X}_{non-obese} - \bar{X}_{obese}$)	(βnon-obese - βnon-obese)$\bar{X}_{obese}$
L.wages	0.226**	7.840	0.252***	8.075	-0.053	-0.212
Age	-0.011	39.533	0.092***	42.772	0.035	-4.401
Age2	0.000	1642.101	-0.001***	1914.781	0.000	1.915
African	-0.196	0.702	0.042	0.846	0.028	-0.201
Colored	-0.451**	0.108	0.235	0.055	-0.024	-0.038
Indian	-0.353*	0.070	-0.239	0.032	-0.013	-0.004
Urban	0.166*	0.710	-0.113	0.687	0.004	0.192
Married	0.128	0.367	-0.458**	0.477	-0.014	0.279
Perceived health	-0.139	1.920	-0.149*	2.120	0.028	0.021
Household size	-0.082**	4.508	-0.063***	4.787	0.023	-0.092
Household income	0.458**	8.990	0.629***	9.168	-0.082	-1.566
Education	0.017	10.479	0.041**	10.591	-0.002	-0.254
Wave1	0.000	0.000	0.000	0.000	0.000	0.000
Wave2	0.000	0.000	0.000	0.000	0.000	0.000
Wave3	0.063	0.479	0.092*	0.466	0.001	-0.014
Constant	2.832**		-1.352			
TOTAL					**-0.069**	**-4.374**
N	230		390			
Difference in constants	4.18366					
TESTS OF EXOGENEITY						
Hansen	Prob > chi2 = 0.432		Prob > chi2 = .111			
Difference	Prob > chi2 = .142		Prob > chi2 = .334			

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimation

C4: MALE WAGES (DYNAMIC GMM)

Males	βnon-obese	$\bar{X}_{non-obes}$	βobese	$\bar{X}_{obese}$	βnon-obese $(\bar{X}_{non-obese} - \bar{X}_{obese})$	(βnon-obese - βnon-obese)$\bar{X}_{obese}$
L.wages	0.024	7.980	-0.048	8.383	-0.010	0.605
Age	0.070**	40.734	0.041	43.332	-0.183	1.274
Age2	-0.001*	1750.9	0.000	1985.8	0.141	-1.191
African	-0.317**	0.883	0.621***	0.921	0.012	-0.864
Colored	-0.376**	0.068	0.538***	0.045	-0.008	-0.041
Indian	-1.755***	0.005	0.000	0.034	0.050	-0.059
Urban	0.078	0.651	-0.046	0.775	-0.010	0.096
Married	-0.306*	0.470	0.101	0.597	0.039	-0.243
Perceived health	-0.021	1.960	-0.062***	1.921	-0.001	0.078
Household size	-0.087***	3.389	-0.100***	3.475	0.008	0.044
Household income	0.776***	8.738	0.940***	9.009	-0.211	-1.476
Education	0.044***	9.587	0.044***	9.873	-0.013	0.001
Wave1	0.000	0.000	0.000	0.000	0.000	0.000
Wave2	0.000	0.000	0.000	0.000	0.000	0.000
Wave3	0.092**	0.437	-0.018	0.471	-0.003	0.052
constant	-0.277		-1.903			
TOTAL					**-0.188**	**-1.725**
N	388		242			
Difference in constants	1.626					
TESTS OF EXOGENEITY						
Hansen	Prob > chi2 = 0.499		Prob > chi2 = 0.372			
Difference	Prob > chi2 = .442		Prob > chi2 = .139			

*p<0,1; ** p<0.05; *** p<0.01

Note: All figures have been weighted using the NIDS panel survey weights that account for between-wave attrition

Source: Authors' own estimations