

**Minor Dissertation**

**Chloe von Widdern**

**Student number: VWDCHL001**

**Supervisor: Reza Daniels**

*Exploring the relationship between obesity and the probability of gaining employment in the context of the South African labour market*

**ECO5023W, University of Cape Town**



The copyright of this thesis vests in the author. No quotation from it or information derived from it is to be published without full acknowledgement of the source. The thesis is to be used for private study or non-commercial research purposes only.

Published by the University of Cape Town (UCT) in terms of the non-exclusive license granted to UCT by the author.

## **ABSTRACT**

Obesity is a growing public health concern that is being confronted by both developed and developing countries. South Africa is no exception, facing the highest burden of obesity amongst African countries. Using two waves of data from the National Income Dynamics Study, this study aims to investigate the relationship between obesity and employment status for working age individuals in the context of the South African labour market. This study contributes to existing literature on this subject by explicitly accounting for potential simultaneity and endogeneity between obesity and employment. Given the hypothesised two-way causal relationship between obesity and unemployment, two different models are used to assess whether this issue exists for the dataset; a bivariate probit model to assess if there is a bivariate relationship between obesity and employment, and a recursive bivariate probit model to assess if obesity is an endogenous regressor of employment. A change in state univariate probit model is then implemented across the two waves to better understand if fluctuations in weight status are a result of labour market state transitions. The results of the study show that obesity and employment are independent in the bivariate probit models and obesity is an exogenous regressor of employment status in the recursive bivariate probit models. Changes in labour market state do not have a significant impact on the probability of transitioning to obese compared to no changes in labour market state, bar transitioning from not economically active to employed, which increases the probability of becoming obese. The findings suggest that, in the South African labour market context, obesity and employment are not related, indicating that there are other underlying factors, such as nutritional intake and genetic composition, that may contribute to fluctuations in weight status. The results suggest that obesity is prolific in South Africa, and impacts individuals across the entire distribution for labour market status and income.

Keywords: Obesity; Employment; Simultaneity; Bivariate relationship; Endogeneity; Bivariate probit; Recursive Bivariate probit

## TABLE OF CONTENTS

<b>1. Introduction</b>	<b>1</b>
<b>2. Literature review</b>	<b>3</b>
<b>3. Analytical methodology</b>	<b>9</b>
3.1 Description of data and variables used	9
3.1.1 Dependent variables	10
3.1.2 Independent variables	11
3.2 Model specification	13
3.2.1 The models	14
<b>4. Results</b>	<b>17</b>
4.1 Descriptive results	17
4.1.2 Transition matrices	21
4.2 Regression results	24
<b>5. Discussion and limitations</b>	<b>34</b>
<b>6. Conclusion</b>	<b>36</b>
<b>7. References</b>	<b>38</b>
I. Appendix	43
IA. Key literature findings	43
IB. Descriptive statistics	49
IC. Regression results	50

## 1. Introduction

Overweight and obesity are growing global public health concerns, and effective policy intervention that attempts to decrease this burden appears to be scarce (Paraponaris, Saliba & Ventelou, 2005; Ardington & Gasealahwe, 2012; Gortmaker *et al*, 2011; Wittenberg, 2011; Lehnert *et al*, 2013; Ng *et al*, 2014; Pienaar 2015; Phelta & Skaal, 2017). Previously thought to be an epidemic faced by developed countries, growing evidence suggests both low- and middle-income countries are also facing the plight (Joubert *et al*, 2007; Some, Rashied & Ohonba, 2016). According to the World Health Organization (WHO), without successful policy intervention, it is estimated that there will be over 1 billion obese adults worldwide by 2025 (World Obesity, 2021).

South Africa (SA) faces the highest burden of obesity amongst African countries (Mickelsfield *et al*, 2013; Some, Rashied & Ohonba, 2016; Tugendhaft *et al*, 2016), with 41% of women and 11% of men being classified as obese in 2016 (South Africa Demographic and Health Survey [NDoH], 2019). An upward trend is exhibited for women, with the mean Body Mass Index (BMI) of women in SA increasing from 27.3kg/m<sup>2</sup> in 1998 to 29.2kg/m<sup>2</sup> in 2016 (NoDH, 2019). The trend is less pronounced for men however, with mean BMI increasing by only 0.2kg/m<sup>2</sup> to 23.6kg/m<sup>2</sup> over the 18-year period (NDoH, 2019).

According to Ogden *et al* (2007), there are genetic, biological, and personal traits which make individuals in a population more susceptible to weight gain and the development of obesity. Genetic predisposition to obesity alone is not enough to explain the rapid increase in the occurrence of obesity (WHO, 1998; Ogden *et al*, 2007; Rosin, 2008). Environmental factors such as sedentary occupations or urbanisation, together with behavioural factors such as overeating or minimal physical exertion, susceptibility to suffering from depressive symptoms, and emotional wellbeing interact with genetic factors, compounding weight-gaining tendencies of those individuals who are genetically more susceptible to obesity (Senekal, Steyn & Nel, 2003).

The nutritional value of food also plays an important role in the prevalence of obesity (Rush & Yan, 2017) - it can be attributable to either malnourishment due to poverty, or overeating. Scarcity of affordable, healthy food items coupled with the lack of effective policy implementation can lead to malnutrition-led obesity in poverty-stricken areas (Ogden *et al*, 2007; Gortmaker *et al*, 2011; Pienaar, 2015). Food addiction together with the rise of fast-food industries can contribute to overeating-led obesity (Gearhardt & Hebebrand, 2021). This is significant in the South African context as the country experiences a high prevalence of both obesity and malnutrition (Mickelsfield *et al*, 2013; Tugendhaft *et al*, 2016).

Notably, some of these underlying factors also influence the ability to gain or maintain employment; specifically, physical, and mental health and emotional wellbeing. This leads to potential issues of simultaneity and endogeneity when attempting to contextualise the impact of obesity on employment (Morris, 2007; Some, Rashied & Ohonba, 2016).

An endogenous relationship between obesity and employment propensity has been well documented in previous literature - the focus has mainly been to identify simultaneity between the two variables and implement models which account for obesity being an endogenous regressor of employment status. Morris (2007) conducts an empirical investigation of the impact of obesity on employment in England using propensity score matching and instrumental variables (IV) in a recursive bivariate probit model to account for simultaneity. In the South African context, Some, Rashied and Ohonba,(2016) closely replicates the methodology developed by Morris (2007) using data from the National Income Dynamics Study (NIDS) and implements Instrumental Variable (IV) estimation using a recursive bivariate model to better account for simultaneity between obesity and employment. Henry and Kollamparambil (2017) investigates the relationship between weight status and employment status using linear probability and probit models to assess the impact endogeneity has on the magnitude of the estimation results.

This study aims to better understand the relationship between obesity and employment status in the context of the South African labour market using data from wave 1 (2008) and wave 2 (2010/11) of NIDS. These two datasets were selected because the Global Financial Crisis occurred in 2008, which resulted in South Africa entering a recession in 2009 (Parliamentary Monitoring Group, 2009). As such, changes in employment status and/or weight status might be exacerbated by this significant event. The focus of this study is twofold: *firstly*, whether a bivariate relationship exists between obesity and employment in the South African context, and if so, whether obesity is an endogenous regressor in the estimation to assess what influences employment propensity, and *secondly*, assuming that the two outcome variables are independent of one another, whether a change in state in labour market status impacts propensity for obesity. The NIDS data only contains information on respondent's weight and height, and as such the nutritional value of the food consumed by respondents cannot be measured. This is a limitation of the study, as neither malnutritional-led nor overeating-led obesity can be observed from the NIDS datasets, and BMI versus nutrient measures of obesity are diametrically different.

This study contributes to existing literature by implementing bivariate and recursive bivariate probit models to test for independence and endogeneity between obesity and employment status, two sets of binary variables. The bivariate model assumes that the error terms of the two equations are unrelated whereas the recursive bivariate model allows for the error terms to be correlated to some degree (Filippini *et al*, 2018). The findings indicate that neither a bivariate relationship nor endogeneity exist between obesity and employment status in the South African context. This allows for a univariate probit model to be implemented to assess whether a change in labour market state causes a transition into obesity across the two waves. The findings of this regression indicate a statistically insignificant causal relationship apart from transition from not economically active to employed, which has a significant and positive impact on the probability of becoming obese. These results could indicate that the domestic problem of obesity is more endemic than might have otherwise been thought. Additional research should be conducted to assess whether the high prevalence of obesity in South Africa is the result of a national overeating problem or malnourishment and poverty, which is a public health emergency.

The rest of the study proceeds with Section 2 discussing the existing literature; Section 3 describing the analytical framework; Section 4 analysing the descriptive statistics and results of the estimated models;

Section 5 presenting a discussion on the estimation results and limitations of the investigation; and Section 6 to conclude.

## 2. Literature review

In a socioeconomically driven world where commercial principles outweigh philanthropic principles, the intent to earn income or make profit primarily motivates individuals. The desire, and more crucially the necessity, to earn money requires some form of employment or self-employment. Existing literature indicates that the ability to gain employment is influenced by obesity status (Morris, 2007; Henry & Kollamparambil, 2017). Obesity, and associated non-communicable diseases (NCDs), can be highly debilitating and give rise to functional limitations (Monteiro *et al*, 2004). It is thus important to consider the relationship between obesity and individuals' employment propensity.

According to WHO, obesity can be defined as a multifaceted disease which arises because of an energy imbalance; where dietary energy consumption surpasses energy expended over a significant period (WHO, 1998; Chooi, Ding & Magkos, 2019). With a positive energy balance, excess calories are converted into fatty acid triglycerides, stored in the body's fat cells in the form of adipose tissue (Chooi, Ding & Magkos, 2019). Over time, this tissue expands, increasing total body fat and causing weight gain (WHO, 1998; Chooi, Ding & Magkos, 2019). Obesity becomes chronic when fat accumulation in the body reaches a threshold which increases risk for several other NCDs, including type 2 diabetes mellitus, cardiovascular diseases, hypertension, strokes, gallbladder disease, musculoskeletal disorders, certain types of cancer and several psychological disorders (Monteiro *et al*, 2004; Paraponaris, Saliba & Ventelou, 2005; Wang *et al*, 2011; Some, Rashied & Ohonba, 2016; Tremmel *et al*, 2017; Chooi, Ding & Magkos, 2019).

A common population-level measure for obesity is an individual's BMI (Kortt, Langley & Cox, 1998). BMI is defined as the individual's weight (in kilograms) divided by their height (in metres) squared (WHO, 1998). According to the National Institute of Health, an individual is classified as: underweight if  $BMI < 18.5 \text{ kg/m}^2$ ; normal weight if  $18.5 \leq BMI < 25 \text{ kg/m}^2$ ; overweight if  $25 \leq BMI < 30 \text{ kg/m}^2$ ; and obese if  $BMI \geq 30 \text{ kg/m}^2$  (Rahman & Berenson, 2010).

Whilst BMI is one of the most popular measures used in social science analyses relating to obesity, several authors have critiqued the accuracy of BMI classifications across different population groups (Kilicarslan *et al*, 2006; Burkhauser & Cawley, 2007; Stevens, McClain & Tuesdale, 2008; Henry & Kollamparambil, 2017). Wittenberg (2011) found that income and body mass increased monotonically for black South Africans such that BMI could be used as an accurate marker for these individuals' well-being, the results for white South African women showed a negative relationship between body mass and economic resources. Classifying individuals as obese using BMI cut-offs has the potential to skew the gap between the proportion of obese individuals based on gender and different population group (Burkhauser & Cawley, 2007). However, Stevens, McClain and Tuesdale (2008) argue that the economic cost of including more accurate measures of adipose tissue must be weighed against the marginal improvements these measures provide in estimating the consequences of obesity.

It is important to consider the impact nutrition plays on obesity and how measures for nutrient in-take can provide diametrically different measures compared to BMI-measurements. Dietary patterns have a significant impact on obesity prevalence, either through malnutrition due to poverty or overeating due to lifestyle habits (Rush & Yan, 2017; Gearhardt & Hebebrand, 2021). Thus, datasets which provide measures that reflect the nutritional composition of food consumed by respondents strengthen analyses of the causes of obesity.

According to WHO (2020), in 2016 ~1.9 billion adults worldwide were estimated to be overweight, with ~650 million adults being classified as obese, cumulatively amounting to 39% of the world's population. Without successful policy intervention to curtail this current trend, it is estimated that by 2025 there will be ~2.7 billion overweight, and ~1 billion obese, adults worldwide (World Obesity, 2021).

Prior to the 1980s, only the United States was thought to have an obesity problem (WHO, 1998), with the percentage of obese individuals increasing from 15% in 1980 to 42.4% in 2018 (Freedman, 2011; Hales *et al*, 2020). Low- and middle-income countries continue to face a double burden of disease with both malnutrition and obesity steadily rising in these countries (Shekar & Popkin, 2020). It is concerning that as GDP per capita increases in developing countries, the burden of these two diseases shifts more towards lower income individuals, such that more than 55% of the global increase in obesity is attributable to rural communities (Shekar & Popkin, 2020). This double burden of disease is particularly true for many African countries, where obesity coexists with undernutrition (WHO, 1998; Drewnowski & Specter, 2004; Rosin, 2008). The Sub-Saharan African region is experiencing the fastest growth in the simultaneous prevalence of malnutrition and obesity (Tathiah *et al*, 2013), with SA currently facing the highest incidence of obesity among African countries (Mickelsfield *et al*, 2013; Some, Rashied & Ohonba, 2016; Tugendhaft *et al*, 2016).

The 2016 South African Demographic and Health Survey published by NDoH (2019) reveals that 27% and 41% of the local female population (15 years and older) were classified as overweight and obese respectively, with one in five women being categorised as morbidly obese. The statistics on overweight and obese South African men in 2016 are lower at 20% and 11% respectively (NDoH, 2019). Given the growing incidence of obesity in women in SA, it is understandable that three of the top four leading causes of death in women, as reported by the Statistics South Africa (StatsSA) *Mortality and causes of death in South Africa* 2018 report, are all comorbidities of obesity – diabetes mellitus, heart disease and hypertensive diseases.

It is estimated that by 2030 NCDs will be the principal cause of death in the African region (Nojilana *et al*, 2016). Further exemplified in Lopez and Murray's 1998 ground-breaking study on the global burden of disease, the authors hypothesised that by 2020, NCDs would account for 70% of all deaths in developing countries, with working-age adults in Sub-Saharan Africa facing the highest probability of death from chronic lifestyle diseases. Increases in risk factors such as smoking, alcohol use, obesity coupled with physical inactivity and unhealthy diets, have led to NCDs becoming more prevalent and burdensome in developing countries (Boutayeb & Boutayeb, 2005; Nojilana *et al*, 2016).

This can in part be attributed to globalisation and advances in technology resulting in both less physical exertion when obtaining food, as well as a nutritional transition (Chooi, Ding & Magkos, 2019). Further, the rise in middle class populations in Sub-Saharan Africa has altered lifestyles and purchasing habits which include alcohol and cigarettes (Lau *et al*, 2018). Altered spending habits, coupled with the growing prevalence of fast-food outlets in southern Africa have also contributed to the growing incidence of obesity. Otterbach *et al* (2021) use wave 5 of NIDS and Google data to determine whether the rapid onset of obesity in South Africa can in part be accountable to the rising numbers of fast-food outlets and supermarkets. The authors find that the proximity to large supermarkets and fast-food outlets increases the probability of adults becoming overweight or obese by 1.2 percentage points and increases individuals' BMI by 0.14 kg/m<sup>2</sup> (Otterbach *et al*, 2021).

When conducting a study on the associated health costs of obesity, Sturm *et al* (2013) found that the burden overweight and obese individuals have on the healthcare system differ significantly, with obese persons having a negative effect, and overweight persons not having an effect. Both Andreyeva *et al* (2004) and Flegal *et al* (2013) found that overweight individuals had a muted effect on healthcare costs and mortality in the United States, yet obese individuals placed a substantial strain on the healthcare system and labour market productivity. This study will therefore focus only on obese individuals as opposed to both overweight and obese people.

In addition to the direct healthcare costs associated with obesity, there are also societal, indirect, and personal costs attributable to obesity (Seidell, 1998). Obesity and to a large extent its associated comorbidities are accountable for decreased productivity, increased employee turnover and training costs, absenteeism, presenteeism, and increased employee disability claims (Some, Rashied & Ohonba, 2016; Tugendhaft *et al*, 2016; Kjellberg *et al*, 2017; Tremmel *et al*, 2017).

Alaba and Chola (2014) find that contributing factors which make an individual more susceptible to obesity as well as exacerbate the progression of the disease include poverty, low-status vocations, and lower educational attainment. These findings are confirmed by those of Adeniyi, Longo-Mbenza and Ter Goon (2015). These authors find female sex, excessive alcohol and soft drinks consumption, rural residence, and unemployment to be positively and significantly associated with obesity. Senekal, Steyn and Nel (2003) found black ethnicity, low educational attainment, infrequent physical activity, and having either an overweight mother or father to all be contributing factors toward the incidence of obesity. Kjellberg *et al* (2017) find income and obesity to be negatively related, with a one unit increase in BMI above 30 leading to a 2% decrease in income.

Cultural beliefs may use weight as a signal under asymmetric information in relation to views on body image (Rosin, 2008). This is especially significant in SA where higher BMIs are accepted among many black women as an indication of wealth, dignity, strength, being treated well by their significant other and good health (Joubert *et al*, 2007). Weight loss amongst black women can be negatively associated with diseases such as HIV/AIDS as well as eating disorders (Joubert *et al*, 2007). According to Kilicarslan *et al* (2006) the occurrence of obesity is still high among low-educated individuals living in urban areas because rural cultural values encourage obesity. Further, when analysing the relationship

between measures of economic well-being and weight status, Wittenberg (2011) found that on average, black South Africans, specifically women, desire a high body mass, and Mchiza *et al* (2005) found that in SA, black women valued a heavier physique compared to that of white or coloured women.

According to Chooi, Ding and Magkos (2019), the rapid rise in the prevalence of obesity is attributable to changes in environmental, socioeconomic, dietary, physical activity, genetic factors, and the interaction between these different factors. Additional factors which impact obesity include mental health and emotional wellbeing (Goldsmith, Verum & Darity, 1996; Kilicarslan *et al*, 2006). However, the interplay between employment status and these variables can in part influence weight status, creating an issue of reverse causality.

The two most significant adverse effects of unemployment are forgone output and income, and psychological impairment through a deterioration in mental health endured by unemployed individuals (Goldsmith, Verum & Darity, 1996). McKee-Ryan *et al* (2005) conclude that unemployed individuals experienced a deterioration in both their psychological and physical well-being compared to their employed counterparts. Further, van der Noordt *et al* (2014) found strong evidence that employment provided a protective effect on depression and mental health in general. Obesity is a prevalent somatic comorbidity of mood disorders, most notably major depressive disorders (Avila *et al*, 2015), likewise obesity greatly exacerbates the risk of being diagnosed with mental disorders (Chooi, Ding & Magkos, 2019).

The systematic review conducted by Hergenrather *et al* (2015) concluded that sustained periods of employment lead to a greater frequency of physical exercise for women. Further, the authors found that overemployed persons suffered from more chronic diseases compared to full-time or part-time employed persons. Finally, the study evidenced that unemployed individuals suffered more health complaints and had poorer physical health compared to employed individuals. Pacheco, Page and Webber (2014) found that activity limiting physical health negatively impacted the ability to gain employment, and the interaction between physical and mental health to have more explanatory power when examining the impact on employment propensity compared to the two health variables separately.

According to Morris (2007), there exists a two-way causal relationship between obesity and (un)employment. The author provides four possible theoretical hypotheses that might explain the impact weight status has on employment and vice versa: firstly, the debilitating health consequences of, and decreased productivity due to, obesity can lead to unemployment; secondly, lower income as a consequence of unemployment can lead to consumption of cheaper, fattening and less healthy foods, which subsequently can cause obesity; thirdly, if unobserved factors that are correlated with both obesity and unemployment are not taken into account, such as time preferences and discounting the future; and fourthly, if measurement error is inherent in the obesity variable, which is due to unobserved factors that are correlated with employment and socioeconomic status (SES) (Morris, 2007). Failure to correctly account for this two-way causal relationship when modelling the impact of obesity on employment leads to endogeneity, and biased and inconsistent estimation results.

Morris (2007) investigated the impact of obesity on employment first by performing a baseline univariate probit that did not account for endogeneity between obesity and employment status using pooled data from two rounds of the Health Survey data for England. Obesity was shown to negatively impact the probability of becoming employed for men and this result was statistically significant. However, for women, obesity had a positive and insignificant impact on the probability of regaining employment. Morris (2007) then used propensity score matching models and recursive bivariate probit models with the prevalence of obesity in the area wherein the respondent lives as the IV to account for endogeneity. The IV marginal effect results show that for both men and women obesity has a negative and statistically significant impact on employment status. The average treatment effect on the treated in the propensity score matching models show the same indirect and significant relationship.

When predicting the social and economic disadvantages such as unemployment, low income, and social isolation of different classifications of weight status of Finnish adults, Sarlio-Lähteenkorva and Lahelma (1999) implemented a logit model to analyse the impact current obesity had on current and long-term employment. The authors found that obesity in women had a significant positive effect on long-term unemployment but an insignificant effect on current employment, whereas for men the impact of obesity on both current and long-term unemployment was insignificant. Sarlio-Lähteenkorva and Lahelma (1999) concluded that deviant (from normal) weight status contributes to both social and economic disadvantages but failed to rule out the possibility of reverse causality.

Laitinen *et al* (2002) evaluated the direction of association between obesity and unemployment by first investigating whether obesity at age 14 is a predictor for sustained unemployment for young adults, and secondly, by considering whether sustained periods of unemployment influence the risk of obesity at age 31 using binary logistics regression analyses. The results show that overweight and obesity at age 14 predicted neither future unemployment at age 31 nor low household income independently. However, the occurrence of the disease in adolescence was associated with poor school performance and it can thus be postulated that obesity indirectly affects the probability of employment through the level of educational attainment achieved (Laitinen *et al*, 2002). Further, sustained unemployment exacerbated the risk of obesity in women, even after controlling for other explanatory variables, as during these repeated periods behavioural factors leading to and maintaining obesity appeared to be reinforced.

Paraponaris, Saliba and Ventelou (2005) analysed how overweight and obesity affect the duration of working years spent unemployed as well as the ability to regain employment based on weight status. The authors consider the effect sustained periods of unemployment may have on change in weight status and mitigate this direct endogeneity problem by using the absolute  $kg/m^2$  difference between the BMI of individuals when they were age 20 and the median BMI for individuals the same age as a proxy for weight status. The results from the probit estimation show that each  $kg/m^2$  deviation from the median BMI increases the probability of becoming unemployed for women, whereas the OLS estimation of the logit transformation shows weight status has a greater impact on the duration of unemployment for men. These results are statistically significant.

Cawley (2004) uses several different regression strategies to estimate the impact of weight status measured as BMI on wages. To account for endogeneity Cawley (2004) uses the lagged value of a subject's BMI as an IV for current BMI as one to account for any contemporaneous effect of wages on weight, as well as a differencing strategy between individuals with highly correlated genes. A strong, negative, statistically significant, relationship between the earnings of white females and body weight was observed by Cawley but the relationship was much weaker for black females (2004). When estimating the relationship between body weight and earnings for men of different ethnicities, Cawley (2004) found the relationship to be positive and significant for black males, and not statistically different from zero for white males. A critique of this instrumental variable approach to correct for endogeneity is that the lagged values of BMI are from seven years prior to the investigation and the time series data itself consists of thirteen years (De Sousa, 2012). Following individuals for so long a time could lead to substantial information loss and make it difficult for researchers with different datasets that have fewer time periods to replicate the methodology of this study.

Lindeboom, Lundborg and van der Klaauw (2010) also use data from the NCDS to estimate the effect of obesity on employment. To account for endogeneity, the authors implement parental obesity as an instrument following the instruments introduced by Cawley (2004) as well as a first differencing strategy first adopted by Baum and Ford in 2004. The baseline linear probability model which assumes exogeneity showed that both men and women who are obese had lower employment probabilities, however the IV results were substantially different. After correcting for endogeneity, Lindeboom, Lundborg and van der Klaauw (2010) found that the relationship between obesity and employment status to be positive but insignificant for both men and women. These results were confirmed on first differences between employment and obesity using panel data regressions and were in line with Norton and Han's (2008) findings of no significant effect of weight status on employment for men and women in the United States.

Past economic and biomedical literature, specifically South African literature, has focused on the prevalence, causes and associated health risks, and socioeconomic disparities of overweight and obesity (Kruger *et al*, 2005; Bennett, Probst & Pumkam, 2011; Flegal *et al*, 2013; Alaba & Chola, 2014; Ng *et al*, 2014), with very few studies investigating the economic cost of overweight and obesity (Abegunde *et al*, 2007; Lal *et al*, 2012; Lehnert *et al*, 2013). More recent South African publications have largely focused on obesity trends and risk factors (Cois & Day, 2015; Pienaar, 2015), the social determinants of obesity such as poverty-level, gender and level of educational (Alaba & Chola, 2014; Adeniyi, Longo-Mbenza & Ter Goon, 2015), and the relationship between a persons' SES and weight status (Wittenberg, 2011). There is a limited body of South African literature which takes into consideration the two-way causal relationship between employment and obesity. Some, Rashied and Ohonba (2016) and Henry and Kollamparambil (2017) both investigate the impact of weight status on employment for South African adults, incorporating models which consider inherent endogeneity.

Some, Rashied and Ohonba (2016) investigate the impact of obesity on employment status in SA. This investigation closely replicates that study done by Morris (2007). The baseline univariate model which assumes an exogenous relationship between obesity and unemployment shows that obesity has a

positive, insignificant effect on the probability of gaining employment for both men and women. Using a likelihood ratio test, Some, Rashied and Ohonba (2016) reject the null hypothesis that obesity is exogenous in the univariate probit model. Subsequently a recursive bivariate probit model with the degree of physical activity, the obesity status of the respondent's head of household, and diagnosed comorbidities associated with obesity as instrumental variables is estimated. The results of the bivariate probit model show that obesity has a substantial negative impact on the probability of employment for both men and women, however the estimate is statistically insignificant for women. Some, Rashied and Ohonba (2016) recommend that future research on this topic focus on using panel data to achieve more robust results.

Henry and Kollamparambil (2017) use the NIDS as a panel dataset to investigate the impact of BMI on employment status and wage levels. The authors use BMI and BMI squared as explanatory variables however, they use different cut-off values to classify different ethnic groups as obese and non-obese as prescribed by Ntuk *et al* (2014). Henry and Kollamparambil (2017) also first run a baseline univariate model which assumes exogeneity and then perform a dynamic system Generalised Method of Moments (GMM) model which takes endogeneity into account, although the authors do not perform separate estimations for males and females. The results from the probit regression show a non-linear relationship between BMI and employment status. Initially increases in BMI increase the probability of gaining employment until a turning point where, thereafter, increases in BMI decrease the probability of employment. The dynamic GMM estimation validates the relationship established by the probit model even after endogeneity is considered, and these estimates are significant at the 10% level. The authors conclude interestingly that the optimal BMI for employment probability is  $30 \text{ kg/m}^2$ .

The principle findings and results of the above literature which examines the relationship between obesity and employment are available in Table A.1 in the Appendix. These summarised findings provide evidence to the issue of independence and endogeneity between obesity and employment in several different labour markets and demonstrate the various models that have been implemented to better account for the issue.

### **3. Analytical methodology**

This section describes the data used in this empirical analysis; construction of the selected variables included in the analysis; and the models used in the empirical investigation.

#### **3.1 Description of data and variables used**

Waves 1 and 2 of NIDS, conducted by the Southern Africa Labour and Development Research Unit, are the datasets used for this empirical investigation. The panel data in these waves reflect trends in obesity and employment statistics for SA between the period 2008 and 2011 and are nationally representative samples of approximately 7 300 and 28 000 South African households and individuals, respectively. Waves 1 and 2 of NIDS formed the basis of this study as the 2008 Global Financial Crisis, an important period in South Africa's history where the country entered a recession in 2009 (Parliamentary Monitoring Group, 2009), occurred between these two waves of data and provides the

opportunity to observe potentially more apparent pre- and post-recession impacts on physical health, mental health, and employment. A caveat to using these two datasets is that wave 2 was subject to considerable scrutiny as regards the fabrication of interviews by enumerators (Finn & Ranchhod, 2017). This adversely impacted ~7% of the overall results, with a disproportionate number of individuals being recorded as 'Not Economically Active' (Finn & Ranchhod, 2017). However, the fabrications were identified whilst the fieldwork was still taking place, allowing for suspicious interviews to be reconducted (Finn & Ranchhod, 2017).

The datasets contain important variables pertinent to this study which impact both obesity and employment including variables pertaining to the measurement of obesity; employment status variables; individual adult control variables, including years of education and ethnolinguistic variables; mental and physical health-related variables; as well as household variables. The panel dataset created with these two waves represent 21 116 individuals who were successfully interviewed in both rounds. Given that the analysis focuses on employment and weight status, the dataset is refined to exclude individuals who: fall outside the working age parameters (outside the bounds of 15 – 64 years); are economically inactive; have missing data; have extreme BMI values (below  $14 \text{ kg/m}^2$  and above  $65 \text{ kg/m}^2$ ); and women who were pregnant at the time of the interview. This results in a final panel dataset of 2850 respondents per wave, and this is the dataset used when conducting the bivariate and recursive bivariate probit models. Whilst this sample size is relatively small and not necessarily nationally representative, the focus of this study is on changes in state in weight status and employment status across the two waves and thus required a balanced panel dataset with weight and employment observations in each wave for the individual to be included in the sample. The transition matrices for changes in weight status and changes in employment status are presented in Section 4.1.2.

Subsequent to performing the bivariate and recursive bivariate probit models, employment status is broadened to include not economically active individuals<sup>1</sup> to understand the transition from non-obese to obese in more granularity. This results in a broadened sample size of 7 214 individuals per wave.

### **3.1.1 Dependent variables**

#### *Employment status*

The investigation seeks to understand that relationship between obesity and unemployment, particularly whether they are interrelated or if endogeneity is inherent between them. Employment status at the time of the interview is thus the dependent variable. For the bivariate and recursive bivariate probit models, employment status is constructed as a binary variable using the broad definition for employment<sup>2</sup>, which takes on the value of one if the individual is in paid employment or self-employed, and zero otherwise. The transitions between these two states across the two waves are shown in below. For the univariate

---

<sup>1</sup> Individuals age 15 years or older who are classified as neither employed or unemployed because they are not actively working nor seeking employment opportunities.

<sup>2</sup> Kingdon and Knight (2001) rigorously investigate the appropriate definition of unemployment in South Africa and find that the broad definition of unemployment is the relevant measure to use as regards policy analysis.

probit model, a variable categorising the labour market transitions between a combination of not economically active, unemployed, and employed across the two waves is used.

### *Obesity measure*

Measurements which take into consideration an individual's total body fat compositions, body fat percentage, fatness and fat-free mass are not available as an alternative measure of relative weight of individuals in the NIDS dataset. Thus, the standard BMI measure as prescribed by WHO (1998) is used to determine which weight status categories (underweight; normal weight; overweight; obese). BMI is constructed using the weight and height variables provided in the NIDS dataset.<sup>3</sup> After this construction, a dummy variable for obesity is created that takes on the value of one if the individual is classified as obese and zero otherwise. Individuals aged 20 onwards are classified as obese if they have a BMI greater than  $30 \text{ kg/m}^2$ . Adolescents aged 15 to 19 are classified as obese if their BMI-for-age is more than two standard deviations above the median following the reference distributions for males and females set out by WHO (De Onis & Blössner, 2003), as was done by Lindeboom, Lundborg and van der Klaauw (2010) and Ardington and Gasealahwe (2012).

Overweight individuals are included in the base category since Sturm *et al* (2013) show that overweight individuals have no significant adverse macro-level impact on an economy. Underweight individuals with a BMI  $< 14 \text{ kg/m}^2$  are not included in the sample, as individuals below this cut-off are considered severely underweight and bordering on anorexia (WHO, 1998). Further, any women who were pregnant at the time of interview are treated as outliers and are thus excluded from the BMI calculation so that average BMI for women is not overestimated. Any additional inconceivable BMI values are excluded from the sample, as was done by Ardington and Gasealahwe (2012) and Kjellberg *et al* (2017).

### **3.1.2 Independent variables**

#### *Individual adult control variables*

Individual attributes including gender, race, relationship status, age, and first language spoken are all control variables. Labour market discrimination based on race is embedded in SA's history. According to Some, Rashied and Ohonba (2016), white individuals are assumed to have a higher probability of becoming employed compared to other racial groups. Further, there is great debate in current literature over the gender-wage gap (Bhorat & Goga, 2013; Henry & Kollamparambil, 2017), and thus gender, which is a dummy variable, is included in the analysis. Further, previous literature finds obesity to have a higher prevalence in the female population for SA.

Relationship status is included to control for the presumed increased effort individuals who are married or in a relationship exert in job search, thereby increasing their probability of becoming employed (Henry & Kollamparambil, 2017). The home language variable can be used as a proxy to identify an individual's ethnolinguistic origin. This is an important aspect to include given that different ethnic groups have

---

<sup>3</sup> Anthropometric measurements are obtained by the interviewer in the NIDS dataset which minimises the chances of weight being under-reported and height being over-reported, and improves the accuracy of BMI (Paraponaris, Saliba & Ventelou, 2005).

different perceptions on weight status, and first (home) language spoken provides an unconfounded cultural effect. It is also expected that probability of becoming employed increases with age up to a point where thereafter the probability decreases (as the individual nears retirement). Thus, both age and age squared are included in the model.

Increases in education are assumed to have favourable outcomes on both the probability of becoming employed and the labour market outcome for individuals (Morris, 2007). Educational attainment is thus included as an explanatory variable given the positive relationship education has with skill acquisition and productivity, which subsequently makes more skilled individuals stronger employment candidates. The level of educational attainment has also been shown to be correlated with weight status (Drewnowski & Specter, 2004; Rosin, 2008).

#### *Health-related variables*

Mental health is impacted by changes in both employment status and weight status (Goldsmith, Verum & Darity, 1996; Chooi, Ding & Magkos, 2019). The NIDS Adult questionnaire contains all ten of the questions on the Center for Epidemiologic Studies Short Depression Scale (CES-D-10), designed to measure the severity of depressive symptomatology on a self-reported scale (Mthembu & Eyal, 2018). There are four possible answers to the CES-D-10 questions ranging from: “rarely or none of the time”; “some of the time”; “a moderate amount of time”; to “all of the time” and are ranked from one to four respectively (Randolf, 1997). A score above 20 is indicative of the respondent exhibiting symptoms associated with mild to severe depression (Randolf, 1997). A mental health index variable is constructed based on the sum of the scores for the ten questions indicating severity of depressive symptoms exhibited.

The relationship between employment, physical health, and weight status is another key consideration. Seidell (1998); Senekal, Steyn and Nel (2003); Joubert *et al* (2007) and Chooi, Ding and Magkos (2019) all confirm a strong association between the prevalence of obesity and poor physical health and physical inactivity. The physical health variable is a binary variable, reflecting either good physical health, or poor physical health. Good physical health is assigned if an individual exercises three or more times per week, consumes alcohol less than two times per week and has not been diagnosed with activity limiting diseases including: high blood pressure; asthma; cancer; diabetes; heart disease or stroke. Limited exercise and frequent consumption of alcohol can contribute to increases in weight, while many of these diseases are also lifestyle diseases and are comorbidities of obesity (Some, Rashied & Ohonba, 2016; Tremmel *et al*, 2017; Chooi, Ding & Magkos, 2019).

Self-perceived emotional wellbeing is an important variable to incorporate into this analysis, particularly with regards weight status, given different cultural beliefs on what a “healthy” weight status is (Kilicarlan *et al*, 2006; Joubert *et al*, 2007; Rosin, 2008). Further, unemployment may play a role in one’s perceived self-worth and thus negatively impact emotional wellbeing (Some, Rashied & Ohonba, 2016; Henry & Kollamparambil, 2017). Emotional wellbeing is coded as a categorical variable based on respondents’ self-perceived health status.

### *Household variables*

Household variables such as household income, number of individuals residing in the household, geographical location of the household, and province the household is situated in are all necessary additional control variables. Household income, adjusted for inflation<sup>4</sup>, can be used as a reflection of the household's economic status and also serves as a proxy for the quality of food that can be afforded by low income versus high income individuals, as low-income earners often cannot afford high quality, nutritional food. However, the nutritional quality of food consumed is not an available measure in the NIDS datasets, consequently, log of household income can try capture the impact a low-quality diet might have on an individual's weight status. Household income is logged to make the interpretation of its effect on the outcome variables easier. Geographical location as regards whether the household is in a rural or urban area, affects job search costs, available job positions, access to and affordability of nutritional food, as well as extent of sedentary lifestyle (Kingdon & Knight, 2001). Certain provinces present a wage premium making job positions in these provinces more favourable and highly sought after. The extent of urbanisation and development of each province also influences job availability as well as weight status.

### **3.2 Model specification**

Given the strong possibility of a two-way causal relationship between obesity and employment propensity, it is important to implement estimation models which account for potential interrelatedness or endogeneity when estimating the impact of obesity on employment propensity and vice versa. Taking the approach of a bivariate probit, as opposed to a univariate probit model, to estimate the impact of obesity on employment probability allows for the possibility that employment propensity and weight status are jointly determined (Rayton, 2006; Dogbe, 2020). A bivariate probit model involves estimating a system of two probit equations with two binary dependent outcomes that are seemingly related (Filippini *et al*, 2018). The covariance between the two error terms provides an indication of whether the two variables are interrelated. A high degree of covariance demonstrates that the two dependent variables are interrelated and that coefficient estimates obtained through joint estimation are superior to those generated by two separate univariate probit models under the assumption that the two outcome variables are independent of one another (Rayton, 2006; Dogbe, 2020).

However, an issue arises when estimating the relationship between employment status and weight status with a bivariate probit model if one of the two dependent binary outcomes is an endogenous regressor in the other equation (Filippini *et al*, 2018). This would require the use of recursive bivariate probit analysis, which allows for the errors terms in the system of equations to be correlated, and for the binary dependent variable of one equation to be an endogenous independent variable of the other equation (Filippini *et al*, 2018).

Exogeneity of obesity ensures that the coefficients from the bivariate probit estimation are unbiased and consistent estimates of the true effect of obesity on employment status (Dogbe, 2020). However,

---

<sup>4</sup> Household income figures are adjusted using the average annual CPI headline index numbers (December 2016 = 100) reported by Statistics South Africa (2021).

given that existing literature provides evidence of a two-way causal relationship between employment status and obesity, endogeneity due to simultaneity (as well as omitted variables and measurement error) may exist. If dependence exists in the bivariate probit model, the assumption of zero conditional mean is violated and the estimates will be biased and inconsistent. This study will thus implement a bivariate probit analysis to test for independence followed by a recursive bivariate probit analysis to test for endogeneity. The analytical framework of the bivariate probit and recursive bivariate probit models are described below.

### 3.2.1 The models

#### *Bivariate Probit Model*

Let  $Y_{1i}$  be a binary variable representing employment status and assume that the population of size  $N$  is indexed by  $i$ .  $Y_{1i}$  takes on the value of one if the individual is employed, and  $Y_{1i}$  takes on the value of zero if the individual is unemployed. Let  $Y_{2i}$  be a dichotomous variable representing weight status.  $Y_{2i}$  takes on the value of one if the individual's  $BMI \geq 30 \text{ kg/m}^2$  and  $Y_{2i}$  takes on the value of zero if the individual's  $BMI < 30 \text{ kg/m}^2$ . Following the technical description of a bivariate probit model by Greene (2003: 710), the general specification for a system of two equations model would be:

$$y_{1i}^* = \beta_1 x'_{1i} + u_{1i} \quad (1)$$

$$y_{1i}^* > 0 \text{ if } Y_{1i} = 1$$

$$y_{1i}^* \leq 0 \text{ if } Y_{1i} = 0$$

$$y_{2i}^* = \beta_2 x'_{2i} + u_{2i} \quad (2)$$

$$y_{2i}^* > 0 \text{ if } Y_{2i} = 1$$

$$y_{2i}^* \leq 0 \text{ if } Y_{2i} = 0$$

where  $y_{1i}^*$  and  $y_{2i}^*$  are unobserved latent continuous variables;  $\beta_1$  and  $\beta_2$  are the vector of coefficients;  $x'_{1i}$  and  $x'_{2i}$  are the vectors of explanatory variables; and  $u_{1i}$  and  $u_{2i}$  are error terms. For the bivariate model to be valid, the error terms must satisfy the conditions of zero conditional mean and constant variance such that:

$$E[u_1 | x_1, x_2] = E[u_2 | x_1, x_2] = 0$$

$$var[u_1 | x_1, x_2] = var[u_2 | x_1, x_2] = 1$$

and  $(u_1, u_2)$  follow a bivariate normal distribution and  $cov(u_1, u_2 | x_1, x_2) = \rho$  such that:

$$(u_{1i}, u_{2i}) \sim \Phi_2 \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

Maximum Likelihood Estimation (MLE) is the method used to estimate the bivariate probit model. The standard univariate probit model assumes that  $Y_1$  and  $Y_2$  are unrelated and as such the errors terms in equations (1) and (2) follow separate standard normal distributions, with a covariance of zero i.e.  $cov(u_{1i}, u_{2i}) = 0$  (Rayton, 2006). The interpretation of the covariance between the two error terms parameter,  $\rho$ , for the bivariate probit model differs from that of the recursive bivariate probit model. If  $Y_1$

and  $Y_2$  are interrelated such that the covariance between the two error terms is a non-zero value,  $\rho$ , it then becomes necessary to use a recursive bivariate model, which relaxes the assumption of independence, to jointly model two binary outcomes which are correlated.

However, if  $Y_2$  is an endogenous regressor in equation (1), a bivariate probit analysis is no longer appropriate as a close to zero or zero value of  $\rho$  will incorrectly reflect no correlation between the two binary variables (Filippini *et al*, 2018). Further, equations (1) and (2) can no longer be estimated as two separate univariate probit models, as the assumption of conditional independence will be violated and the parameter  $\beta$  will produce biased and inconsistent estimates (Greene, 2003).

#### *Recursive Bivariate Probit Model*

To test for endogeneity, a recursive bivariate model can be estimated. A recursive bivariate model involves two probit equations where one of the two binary dependent variables is included as a regressor in the other equation, and as such the two error terms are correlated (Maddala, 1983; Greene, 2003). The recursive bivariate model implemented in this study follows the specification of Wilde (2000), where one of the outcome variables is dropped from the other equation. Wilde (2000) critiqued Maddala's (1983) model specifications, claiming that exclusion restrictions are not required on condition that both equations contain one varying exogenous regressor. Consequently, the addition of instrumental variables is not required in the reduced form equation (Li, Poskitt & Zhao, 2019). This specification is taken as sufficient to identify the recursive bivariate probit model in this instance. It is assumed that the identification behind the recursive bivariate probit model using the specification suggested by Wilde (2000) is sufficient when using the omission of the one outcome variables. However, Li, Poskitt and Zhao (2019) cite that including additional instruments into the model could be valuable, although this is beyond the scope of this dissertation in this particular application.

Existing literature has established that weight status is affected by employment status, making the binary weight status variable ( $Y_2$ ) an endogenous variable in the set of equations:

$$y_{1i}^* = \delta y_{2i} + \beta_3 x'_{3i} + \varepsilon_{1i} \quad (3)$$

$$y_{1i}^* > 0 \text{ if } Y_{1i} = 1$$

$$y_{1i}^* \leq 0 \text{ if } Y_{1i} = 0$$

$$y_{2i}^* = \beta_2 x'_{2i} + u_{2i} \quad (4)$$

$$y_{2i}^* > 0 \text{ if } Y_{2i} = 1$$

$$y_{2i}^* \leq 0 \text{ if } Y_{2i} = 0$$

$$(\varepsilon_{1i}, u_{2i}) \sim \Phi_2[(0, 0), (1, 1), (\rho)]$$

where  $\delta$  is a coefficient vector of the effect of weight status on employment status;  $\varepsilon_{1i}$  and  $u_{2i}$  are error terms that are not necessarily independent of one another but are independent of  $x'_{1i}$  and  $x'_{2i}$ ; and the error terms are described by  $\Phi_2$ , a bivariate standard normal distribution, with zero conditional mean, constant variance, and a correlation of  $\rho$ . Equation 4 in this system is the same as equation 2 in the

bivariate probit model system. Once again, the estimation method used to estimate this model is MLE. Importantly,  $\rho$  captures the correlation between the two error terms of equations (3) and (4), whilst  $\delta$  reflects the correlation between  $Y_1$  and  $Y_2$  (Filippini *et al*, 2018).

A Wald test can be performed to test for endogeneity between employment status and weight status. If the null hypothesis of  $\rho = 0$  is accepted, the model consists of independent probit equations (i.e., the error terms of the two equations are not correlated) such that equations (1) and (2) from the bivariate probit model can be estimated separately (Greene, 2003). However, if  $\rho \neq 0$  this indicates endogeneity in the model and the system of equations in (1) and (2) need to be estimated as a recursive model of simultaneous equations. The test for exogeneity can be set out as:

Null hypothesis  $H_0: \rho = 0$

Alternative hypothesis  $H_1: \rho \neq 0$

Where the Wald test follows a Chi-square distribution, and the null hypothesis is rejected if  $W > \chi^2_{(1,\alpha)}$ .

The joint distribution of  $Y_1$  and  $Y_2$  (conditional on  $x'_{2i}$  and  $x'_{3i}$ ) has four outcomes:

$$\left. \begin{aligned} P_{11} &= P(Y_1 = 1, Y_2 = 1 | x'_{3i}, x'_{2i}) = \Phi_2(\delta y_{2i} + \beta_3 x'_{3i}, \beta_2 x'_{2i}, \rho) \\ P_{10} &= P(Y_1 = 1, Y_2 = 0 | x'_{3i}, x'_{2i}) = \Phi_2(\beta_3 x'_{3i}, -\beta_2 x'_{2i}, -\rho) \\ P_{01} &= P(Y_1 = 0, Y_2 = 1 | x'_{3i}, x'_{2i}) = \Phi_2(-\delta y_{2i} - \beta_3 x'_{3i}, \beta_2 x'_{2i}, -\rho) \\ P_{00} &= P(Y_1 = 0, Y_2 = 0 | x'_{3i}, x'_{2i}) = \Phi_2(-\beta_3 x'_{3i}, -\beta_2 x'_{2i}, \rho) \end{aligned} \right\} (5)$$

In the recursive bivariate probit model,  $Y_1$  and  $Y_2$  are dependent on each other through the parameters  $\delta$  and  $\rho$ . Log-likelihood estimation based on the above equations is used to obtain the coefficients:

$$\ln L(\beta_3, \beta_2, \delta, \rho) = \sum_{i=1}^N [Y_1 Y_2 \ln P_{11} + (1 - Y_1) Y_2 \ln P_{10} + (1 - Y_2) Y_1 \ln P_{01} + (1 - Y_1)(1 - Y_2) \ln P_{00}] \quad (6)$$

(Dogbe, 2020) where thereafter, the marginal effects of the coefficients can be derived and are interpreted in the results section.

#### Univariate Probit Model

If it is shown that *firstly*, obesity and employment status are independent when estimating the bivariate probit model, and *secondly*, that obesity is not an endogenous regressor in equation (3), nor employment status in an equation where obesity propensity is the dependent variable, an analysis to understand what influences the transition from non-obese to obese can be performed.

A univariate probit model can be used to model the impact of transitions in states, for examples labour market states or obesity and non-obesity. This is one of the strengths of panel data. In this study, a univariate probit model is used to model the impact that transitions in labour market states between wave 1 and wave 2 of NIDS have on the probability of transitioning from non-obese to obese over the two-year period. Panel data is used to perform this analysis. Panel data can also control for unobserved individual heterogeneity, where failure to control for this could result in inconsistent estimates and inaccurate statistical interpretation (Bartolucci, Belotti & Peracchi, 2015).

For this model, let  $Y$  be a binary variable taking on the value one if an individual was non obese in wave 1 and transitioned to obese in wave 2, and zero otherwise. Further, let  $B$  be a categorical variable representing labour market transitions across wave 1 and wave 2, where  $B$  takes on the value of zero if no change in state occurs.<sup>5</sup> Assuming  $Y$  is a linear function of  $B$  and the same set of explanatory variables included in both the bivariate and recursive bivariate models, for individual  $i$ , the equation can then be modelled using the methodology of Greene (2004) as:

$$y_i^* = \alpha + \lambda B_i + \beta_i X_i + u_i \quad (7)$$

$$y_i^* > 0 \text{ if } Y = 1$$

$$y_i^* \leq 0 \text{ if } Y = 0$$

where  $y_i^*$  is an unobserved latent continuous variable;  $\lambda$  and  $\beta$  are coefficients;  $X$  represents the set of individual adult control variables;  $u$  represents the error term. Equation 7 contains explanatory variables that are either changes in state, or fixed.

#### 4. Results

This section first analyses the descriptive statistics of key variables used in the models, as well as transition matrices to assess underlying causes for changes in state as regards obesity and employment. Thereafter, the results from the bivariate probit and recursive bivariate probit models for each wave are described. Finally, the results from the change in state univariate probit regression are reported. All results in the bivariate and recursive bivariate probit models are weighted using post stratification weights. Panel weights are used for the univariate probit model.

##### 4.1 Descriptive results

Table 1 below shows the frequency and percentage of employed males and females by weight status from the sample across the two waves. As can be seen in the table, only 5.88% and 6.79% of unemployed males in wave 1 and wave 2, respectively, are obese. Whilst this is in line with the literature, despite the dataset being dated, the limited sample size prevents separate probit models being performed for each gender.

Of the sample of males who are employed, majority are not obese (88.42% in wave 1 and 84.49% in wave 2). The same trend is exhibited for unemployed males – 94.12% and 93.21% of the sample of unemployed males are not obese in wave 1 and wave 2, respectively. This trend is less pronounced for females. There is an almost even split between obese (54.59% and 51.62%) and non-obese (45.41% and 48.38%) employed females in the sample across both waves. However, a larger proportion of unemployed females are not obese across both waves (67.21% in wave 1 and 62.45% in wave 2).

---

<sup>5</sup> See Table 6: *Changes in labour market state between wave 1 and wave 2*, for the different categories that  $B$  takes on a value for.

**Table 1: Employment by obesity category and gender for wave 1 and wave 2**

	Males				Females			
	Not Obese		Obese		Not Obese		Obese	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
<b>Wave 1</b>								
Employed	893	88.42%	117	11.58%	547	54.59%	455	45.41%
Unemployed	272	94.12%	17	5.88%	369	67.21%	180	32.79%
<b>Wave 2</b>								
Employed	861	84.49%	158	15.51%	556	51.62%	521	48.38%
Unemployed	261	93.21%	19	6.79%	296	62.45%	178	37.55%

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

Selected means and proportions across employment and weight status for males and females are reported in Table 2 below. The means and proportions of all variables used in the analysis can be found in Table B.1 of the Appendix. One caveat to this analysis is the limited sample size of unemployed obese males in the finalised panel dataset. This prevents analysing the impact of obesity on employment propensity using separate models for males and females in this investigation. Rather, gender is included as an explanatory variable in the models.

It is evident across both waves that the mean BMI for both employed and unemployed males is within normal range – 24.41kg/m<sup>2</sup> and 22.49kg/m<sup>2</sup>, respectively. This is in comparison to females, where the mean BMI for both employed and unemployed females is 30.3kg/m<sup>2</sup> (obese) and 28.05kg/m<sup>2</sup> (overweight), respectively. Further the mean BMI for non-obese and obese females is over 1.4kg/m<sup>2</sup> and 2.3kg/m<sup>2</sup> higher than the mean BMI for non-obese and obese males for both waves. These results are in line with previous literature findings and demonstrate that the mean BMI for men and women differs significantly in SA. Interestingly, the mean BMI for employed males (24.41kg/m<sup>2</sup> and 24.96kg/m<sup>2</sup>) and females (30.03 kg/m<sup>2</sup> and 30.53 kg/m<sup>2</sup>) is higher than the mean BMI for unemployed males (22.49kg/m<sup>2</sup> and 23.22kg/m<sup>2</sup>) and females (28.05kg/m<sup>2</sup> and 28.73kg/m<sup>2</sup>) across both waves, which contradicts literature findings that suggest unemployment results in weight gain.

Looking at the proportion of population group, the African (~20%) and Indian/Asian (23% and 16%) sub-categories have the greatest proportions of unemployed males across both waves, whereas the greatest proportions of unemployed females occur in African (39% and 31%) and Coloured (28% and 31%). However, the largest proportions of obese males occur in the White (30% and 42%) sub-category, and African (42% and 47%) and White (47% 50%) sub-categories for females.

For emotional wellbeing, physical health and mental health, majority of males are employed and non-obese for each sub-category of emotional wellbeing, physical health, and mental health. The lack of variation in proportions of males across employed versus unemployed and non-obese versus obese could be a result of the limited sample size of unemployed, obese males. However, for females, there is more variation. Looking at emotional wellbeing, there is a greater proportion of obese females (55% and 53%) who have poor to fair emotional wellbeing across both waves, compared to non-obese females. Similarly, majority of females with excellent emotional wellbeing across both waves are non-obese (64% and 59%). This is in line with the findings of previous literature.

A greater proportion of females with poor physical health are obese across both waves (44% and 48%) whereas a smaller percentage of women with good physical health are obese in wave 1 and 2 (28%

and 33%). This is in line with previous literature findings. For both emotional wellbeing and physical health the majority proportions of each sub-category occur for non-obese and employed females in both waves. This suggests that emotional wellbeing and physical health are not necessarily adversely impacted by sustained unemployment. However, there is a significant proportion of females who present symptoms that suggest they are often depressed who are unemployed in wave 1 (41%), and this trend continues in wave 2 with 68% of females who present symptoms that classify them as always depressed dealing with unemployment.

These descriptive results indicate that underlying factors that are associated with obesity and unemployment as regards mental and physical health, and emotional wellbeing differ for males and females.

**Table 2: Selected means and proportions for wave 1 and wave 2**

	Males (n=1 299)								Females (n=1 551)							
	Wave 1				Wave 2				Wave 1				Wave 2			
	Employed	Unemployed	Non-Obese	Obese	Employed	Unemployed	Non-Obese	Obese	Employed	Unemployed	Non-Obese	Obese	Employed	Unemployed	Non-Obese	Obese
<b>BMI (kg/m<sup>2</sup>)</b>	24.41	22.49	22.85	33.74	24.96	23.22	23.02	33.88	30.03	28.05	24.52	36.06	30.53	28.73	24.48	36.63
<b>Population group (%)</b>																
African	0.80	0.20	0.90	0.10	0.79	0.21	0.87	0.13	0.62	0.39	0.58	0.42	0.69	0.31	0.53	0.47
Coloured	0.85	0.15	0.89	0.11	0.93	0.07	0.89	0.11	0.72	0.28	0.65	0.35	0.69	0.31	0.64	0.36
Indian/Asian	0.77	0.23	0.94	0.06	0.84	0.16	1.00	0.00	0.82	0.18	0.69	0.31	0.93	0.07	0.73	0.27
White	0.97	0.03	0.70	0.30	0.98	0.02	0.58	0.42	0.90	0.10	0.53	0.47	0.98	0.02	0.50	0.50
<b>Emotional Wellbeing (%)</b>																
Poor / Fair	0.90	0.10	0.82	0.18	0.75	0.25	0.87	0.13	0.61	0.39	0.45	0.55	0.75	0.25	0.47	0.53
Good / Very Good	0.82	0.18	0.88	0.12	0.85	0.15	0.86	0.14	0.66	0.34	0.59	0.41	0.72	0.28	0.52	0.48
Excellent	0.76	0.24	0.92	0.08	0.79	0.21	0.84	0.16	0.63	0.37	0.64	0.36	0.72	0.28	0.59	0.41
<b>Physical Health (%)</b>																
Poor physical health	0.82	0.18	0.87	0.13	0.82	0.18	0.86	0.14	0.63	0.37	0.56	0.44	0.72	0.28	0.53	0.48
Good physical health	0.78	0.22	0.92	0.08	0.80	0.20	0.83	0.17	0.71	0.29	0.72	0.28	0.75	0.25	0.67	0.33
<b>Mental Health (%)</b>																
Always Depressed	0.88	0.12	1.00	0.00	0.45	0.55	0.55	0.45	0.64	0.36	0.68	0.32	0.32	0.68	1.00	0.00
Often Depressed	0.74	0.26	0.91	0.09	0.75	0.25	0.83	0.17	0.59	0.41	0.59	0.41	0.81	0.19	0.46	0.54
Occasionally Depressed	0.82	0.18	0.88	0.12	0.82	0.18	0.85	0.15	0.68	0.32	0.58	0.42	0.71	0.29	0.56	0.45
Never Depressed	0.89	0.11	0.91	0.09	0.91	0.09	0.87	0.13	0.43	0.57	0.63	0.37	0.57	0.43	0.69	0.31
<b>Sample size (n)</b>	<b>1 010</b>	<b>289</b>	<b>1 165</b>	<b>134</b>	<b>1 019</b>	<b>280</b>	<b>1 122</b>	<b>177</b>	<b>1 002</b>	<b>549</b>	<b>916</b>	<b>635</b>	<b>1 077</b>	<b>474</b>	<b>852</b>	<b>699</b>

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

#### 4.1.2 Transition matrices

Whilst this study seeks to identify whether simultaneity and endogeneity exist between employment status and obesity, observing the transition between weight status; employment status; weight and employment status; and labour market status, can provide an early indication of where the greatest variation (and lack thereof) is occurring. A significant change in weight or employment status such that a person transitions from non-obese or employed to obese or unemployed, or vice versa, can be a strong indication of a disruptive event linked to physical or mental health, emotional wellbeing, or a combination of these factors (Senekal, Steyn & Nel, 2003; Ogden *et al*, 2007; Rosin, 2008; Dowdall, Ward & Lund, 2017; Chooi, Ding & Magkos, 2019). Further transitions in labour market status might impact the propensity of an individual to experience a drastic change in weight status.

In transition matrices, no change in state over two time periods is represented by observing 100% along the diagonal of the matrix. Proportions which substantially differ from unity can provide information on underlying relationships influencing obesity or unemployment.

The following presents a discussion on the transition matrices for weight status and broad employment status, which are the two outcome variables used in the bivariate and recursive bivariate probit models. Thereafter, the transition matrix for labour market status is discussed, as this is the main explanatory variable for the univariate probit model.

##### *Transition matrix with weight status:*

Table 3 below indicates that majority of individuals that are not obese in wave 1 maintain this weight status in wave 2 (86.4%). Likewise, majority of individuals who are obese in wave 1 remain obese in wave 2 (77.1%). 13.6% of the sample transitions from not obese to obese across the two waves, and 23% of individuals transition from obese to not obese across the two waves. The moderate changes in weight status between wave 1 and wave 2 suggest that underlying factors, other than changes in employment status, such as physical and mental health and emotional wellbeing could contribute to significant fluctuations in weight status as is suggested by some of the literature findings.

**Table 3:** *Transition matrix with weight status*

Weight Status in Wave 1	Weight Status in Wave 2		
	Not Obese	Obese	Total
Not Obese	1 798 86.4%	283 13.60%	2 081 100%
Obese	176 22.89%	593 77.11%	769 100%
Total	1 974 69.26%	876 30.74%	2 850 100%

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

*Transition matrix with employment status:*

Table 4 below details transitions in broad employment status across wave 1 and wave 2 of NIDS. There is little variation between wave 1 and wave 2 for employed individuals, with 83.6% of individuals maintain their status as employed across the two times periods. As regards, for unemployment, there is a significant amount of variation. Only 50.5% of individuals remain unemployed across both time periods, whereas 49.5% of unemployed individuals in wave 1 find employment in wave 2. Further, only 16.5% of employed individuals in wave 1 transition to unemployed in wave 2. This could indicate that once individuals find employment, there are able to maintain this status in the long-term. The significant increase in employment in wave 2 for wave 1 unemployed individuals could also be indicative of the economic recovery experienced after the 2008 financial crisis.

**Table 4:** *Transition matrix with employment status*

Employment Status in Wave 1	Employment Status in Wave 2		
	Employed	Unemployed	Total
Employed	1 681 83.55%	331 16.45%	838 100%
Unemployed	415 49.52%	423 50.48%	2 012 100%
Total	2 096 73.54%	754 26.46%	2 850 100%

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

*Transition matrix with obesity and employment:*

The most stable state in Table 5 is “not obese and employed”; 70.28% of individuals in wave 1 who are non-obese and employed remain non-obese and employed in wave 2. Likewise, 66.96% of individuals who were obese and employed in wave 1 remained obese and employed in wave 2. This indicates a high degree of correlation.

Conversely, 9.97% of employed, obese individuals became unemployed in wave 2, whereas 15.76% of individuals who were non-obese and employed in wave 1 became unemployed in wave 2. This suggests that non-obese individuals have a 36.74% higher likelihood of transitioning out of employment compared to obese individuals. This also indicates a high degree of variation between employed obese individuals in wave 1 and unemployed obese respondents in wave 2 and suggests factors other than employment status are related to the change in weight status.

Given that the highest proportions are seen in elements where there is no change in state between employment and non-obese/obese, there should be a focus on the elements in the transition matrix with the smallest proportions. Transitioning from not obese and employed to obese and unemployed, and transitioning from obese and unemployed to not obese and employed, are two of the most unstable states (2.01% and 6.60% respectively) and indicate there may be other factors correlated with these transitions such as physical and mental health and emotional wellbeing.

**Table 5: Transition matrix with obesity and employment**

Weight and Employment Status in Wave 1	Weight and Employment Status in Wave 2				
	Not Obese & Employed	Not Obese & Unemployed	Obese & Employed	Obese & Unemployed	Total
Not Obese & Employed	1 012 70.28%	227 15.76%	172 11.94%	29 2.01%	1 440 100%
Not Obese & Unemployed	278 43.37%	281 43.84%	44 6.86%	38 5.93%	641 100%
Obese & Employed	114 19.93%	18 3.15%	383 66.96%	57 9.97%	572 100%
Obese & Unemployed	13 6.60%	31 15.74%	80 40.61%	73 37.06%	197 100%
Total	1 417 49.72%	557 19.54%	679 23.82%	197 6.91%	2 850 100%

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

#### *Transition matrix with labour market state*

Given that using broad employment and weight status results in a small sample size across the two waves, broad employment is expanded to include not economically active individuals when performing the univariate probit model with panel data. Table 6 below shows little variation in the not economically active and employed states, with 71.9% of individuals remaining not economically active, and 59.2% of individuals remaining employed across the two waves. However, there is significant variation in the unemployed state, with only 27.9% of unemployed individuals in wave 1 remaining in this state in wave 2. Further, 44.7% of unemployed individuals in wave 1 transitioning to not economically active in wave 2. This could signify individual's becoming discouraged, which might impact their weight status. Contrastingly, 27.4% of unemployed individuals in wave 1 find employment in wave 2, which could also have a subsequent impact on their weight status. This motivates for an exploration of which changes in labour market states impact a transition from non-obese to obese, which is investigated in the univariate probit model.

**Table 6: Changes in labour market state between wave 1 and wave 2**

Labour Market State in Wave 1	Labour Market State in Wave 2			
	Not Economically Active	Unemployed	Employed	Total
Not Economically Active	2 056 71.89%	439 15.35%	365 12.76%	2 860 100%
Unemployed	677 44.69%	423 27.92%	415 27.39%	1 515 100%
Employed	827 29.13%	331 11.66%	1 681 59.21%	2 839 100%
Total	3 560 49.35%	1 193 16.54%	2 461 34.11%	7 214 100%

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

## 4.2 Regression results

Key results for each of the three models discussed in the methodology are presented below. Detailed estimation output for each probit model and corresponding marginal effects can be found in Tables C.1-C.7 in the Appendix.

### *Bivariate Probit Models*

The principal results for the bivariate probit models for wave 1 and wave 2 are shown in Table 7 below.<sup>6</sup> The bivariate probit model is set up that firstly whether an individual is obese or not is regressed on the full set of explanatory variables and the binary variable, broad employment, is omitted. Thereafter, broad employment is regressed on the same set of explanatory variables, and the binary variable, obese, is omitted. This specification econometrically identifies the model and allows for simultaneity to be directly tested.

The Wald test statistics for the bivariate probit models are 0.26 and 0.29 for wave 1 and wave 2, respectively. Since the p-value for both waves is larger than 0.1, (0.68 for wave 1 and 0.59 for wave 2) the null hypothesis that the covariance between the two error terms is zero cannot be rejected. This implies that the error terms between the two equations are unrelated since rho is not statistically different from zero, and thus the two equations are unrelated i.e., there is no bivariate relationship between obesity and employment. This result is validated by the value of correlation parameters, which are positive, yet close to zero ( $\hat{\rho} = 0.029$  for wave 1 and  $\hat{\rho} = 0.030$  for wave 2). According to Filippini *et al* (2018), the correlation parameter for a bivariate probit model takes on the value of zero if there is no correlation observed between the error terms in the recursive bivariate probit model. As such, the bivariate model does not increase the accuracy of the coefficients and the two equations can be estimated separately.

The coefficients of the explanatory variables in the bivariate probit models indicate the direction and significance that each variable has on the probability of being obese or employed. Only the coefficients from the marginal effects can indicate the magnitude of each variable, however, this is not the principal focus of these models. Table 7 shows that age (represented by a positive parabolic relationship), gender, relationship status, and log of household income all have a significant impact on obesity across both waves. Notably, females have a far greater probability of being obese, with this result being significant at the 1% level. Being in a relationship is shown to increase the probability of being obese, as opposed to being single. Home language, as a proxy for ethnolinguistic characteristics does not have a significant impact on the probability of being obese, and log of household income, a proxy for the quality for food that individuals are able to afford, has a positive impact on the probability of being obese. These results are opposite to those hypothesised in the literature review. However, a possible explanation for the positive impact the log of household income has on obesity is the findings by Otterbach *et al* (2021) and individuals receiving more income being able to afford more (and potentially unhealthy) food at fast-food outlets and supermarkets. Interestingly, home language as a proxy for

---

<sup>6</sup> See Tables C.1 and C.2 in the Appendix for the detailed results of the bivariate probit models and marginal effects, respectively.

ethnolinguistic characteristics does not have significant explanatory power when estimating the probability of being obese. This could indicate that there are more nuanced reasons for obesity persisting across various demographic groups, such as genetic composition, metabolic rate or spending habits on food (Otterbach *et al*, 2021; Chooi, Ding and Magkos, 2019; Rush & Yan, 2017).

Looking at broad employment, gender, household size and log of household income all significantly impact the probability of being employed across both waves. Interestingly, females have a higher probability of being employed, compared to males, with this result being significant at the 1% level. Increases in household size are also shown to increase the probability of being employed. The intuition behind this could be that larger households have more dependents living in them and thus the need to find and maintain employment as a provider is greater. Log of household income also positively impacts the probability of being employed, with this result being significant at the 1% level.

**Table 7:** Selected Bivariate Probit estimation results for wave 1 and wave 2

	Wave 1		Wave 2	
	Bivariate Probit		Bivariate Probit	
	Coef.	Sig.	Coef.	Sig.
Obese				
Broad Employment	-	-	-	-
Age	0.097	***	0.070	**
Age squared	0.001	***	0.001	
Gender	1.073	***	0.964	***
Race				
Coloured	0.319		0.046	
Asian/Indian	0.689		1.256	**
White	0.258		0.048	
Settlement	0.001		0.107	
Relationship status	0.177	**	0.300	***
Province				
Eastern Cape	-0.018		0.233	
Northern Cape	0.038		0.059	
Free State	0.077		0.376	
KwaZulu-Natal	0.166		0.660	**
North West	0.045		0.226	
Gauteng	0.077		0.237	
Mpumalanga	0.114		0.407	
Limpopo	0.360		0.304	
Education	0.014		0.054	***
Household size	0.014		0.003	
Log household income	0.152	***	0.098	**
Home language				
IsiXhosa	0.085		0.184	
IsiNdebele	-0.349		-0.260	
Sepedi	0.099		-0.071	
Sesotho	0.031		-0.052	
Setswana	-0.230		0.021	
SiSwati	-0.134		-0.080	
Tshivenda	-0.604		-0.001	
IsiTonga	-0.387		-0.269	
Afrikaans	0.277		0.718	
English	-0.211		-0.313	
Emotional wellbeing				
Good / Very good	0.201	*	0.028	
Excellent	0.357	***	0.017	

Physical health	0.307	***	0.190	
Mental health				
Often Depressed	0.178		0.837	
Occasionally depressed	0.217		0.578	
Not depressed	0.133		0.613	
<hr/>				
Broad Employment				
<hr/>				
Obese	-	-	-	-
Age	0.038		0.108	***
Age squared	0.000		0.001	***
Gender	0.551	***	0.259	***
Race				
Coloured	0.496	*	0.355	
Asian/Indian	-1.328	***	1.159	**
White	0.261		-0.026	
Settlement	0.039		0.185	*
Relationship status	0.067		-0.185	**
Province				
Eastern Cape	0.484	**	0.051	
Northern Cape	0.688	***	0.037	
Free State	1.229	***	-0.008	
KwaZulu-Natal	0.507	*	0.047	
North West	0.967	***	0.043	
Gauteng	0.915	***	0.019	
Mpumalanga	0.967	***	0.142	
Limpopo	0.936	***	0.112	
Education	0.015		0.018	
Household size	0.108	***	0.117	***
Log household income	0.716	***	0.594	***
Home language				
IsiXhosa	-0.324		0.292	
IsiNdebele	0.167		-0.045	
Sepedi	0.065		0.024	
Sesotho	0.126		-0.136	
Setswana	0.085		-0.056	
SiSwati	0.551	*	-0.166	
Tshivenda	0.479		0.042	
IsiTonga	0.360		0.178	
Afrikaans	-0.121		0.257	
English	0.270		0.907	**
Emotional wellbeing				
Good / Very good	0.002		0.230	
Excellent	0.084		0.167	
Physical health	0.088		0.134	
Mental health				
Often Depressed	0.155		0.771	*
Occasionally depressed	-0.038		0.669	
Not depressed	0.663		0.750	
<hr/>				
Observations	2850		2850	
Pseudo $R^2$	0.0297		0.0304	
Rho ( $\rho$ )	0.0297		0.0304	
Wald test $\rho = 0$		$\chi^2(1) = 0.2624$		$\chi^2(1) = 0.2878$
(p-value)	[0.6085]		[0.5916]	

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Reference categories for categorical variables: Gender (Male); Race (African); Settlement (Rural); Relationship (Single); Province (Western Cape); Home language (IsiZulu); Emotional wellbeing (Poor); Physical health (Poor); Mental health (Always depressed)  
Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

### *Recursive Bivariate Probit Models*

The principle results for the recursive bivariate probit models for wave 1 and wave 2 are shown in Table 8 below.<sup>7</sup> The recursive bivariate probit model is modelled so that obesity is regressed on all explanatory variables in the first stage (this produces identical coefficients as to those in the first section of results in Table 7, where obesity is the outcome variable). In the second stage, employment status is regressed on obesity and all other explanatory variables (producing the results in Table 8). Unlike Some, Rashied and Ohonba (2016) no instrument(s) is included in the recursive bivariate as the recursive bivariate probit model is econometrically identified by omitting one of the outcome variables (in this instance broad employment in the first stage of the regression).

Although the bivariate probit models indicate an insignificant rho, there could still be an underlying relationship between obesity and employment status, which is why it is important to further test for this using the recursive bivariate probit model (Filippini *et al*, 2018). The p-values of the Wald test statistics for the recursive bivariate probit models are 0.94 for the wave 1 model and 0.83 for the wave 2 model. As such, the issue of endogeneity is not statistically significant in these models. This implies obesity is not an endogenous binary regressor of employment status, with this finding being validated by the fact that the coefficient of  $\delta$  ( $\hat{\delta} = 0.01$  in wave 1 and  $\hat{\delta} = 0.10$  in wave 2) is not statistically significant in either model, even at the 10% level. This is in line with the findings of Wilde (2000), where he demonstrated that the identification issue of endogeneity of the one dependent discrete variable can be removed if the other dependent variable is an exogenous regressor in just the one equation.

Further, the correlation parameter in both recursive bivariate probit models is positive, yet close to zero ( $\hat{\rho} = 0.02$  for wave 1 and  $\hat{\rho} = 0.09$  for wave 2). This is in line with the findings of Filippini *et al* (2018), which suggest that if no correlation between error terms is present in the recursive bivariate model, then the direction and magnitude of the correlation parameter will be determined by the value of  $\hat{\delta}$ , which would be zero in the case of exogeneity. This is true for both waves. In wave 1, if the value of  $\hat{\delta}$  is rounded to one decimal, it equals zero, as does the value of  $\hat{\rho}$ . For wave 1, both  $\hat{\delta}$  and  $\hat{\rho}$  take on the same sign and value when rounded to one decimal place. The zero (wave 1) and close to zero (wave 2) correlation parameter of the bivariate probit models implies that the two variables are independent of one another and can be modelled using separate univariate probit models.

In table C.5 in the Appendix, the recursive bivariate probit model is run where the employment and obesity variables are swapped around such that employment status is a regressor of probability of becoming obese. Once again, the null hypothesis of exogeneity cannot be rejected implying that even when the estimation is performed in the opposite direction, employment status is not an endogenous regressor of obesity. This is opposite to the findings of Some, Rashied and Ohonba (2016) who reject the null hypothesis of exogeneity in their recursive bivariate model for males, but only at the 10% level.

---

<sup>7</sup> See Tables C.3 and C.4 in the Appendix for the detailed results of the recursive bivariate probit models and marginal effects, respectively.

Along with gender, household size, and log of household income, certain demographics, provinces, and home languages all present as significant factors which impact the probability of being employed in wave 1. This, however, is not the case in wave 2 and could be an indication of the potential adverse impacts of interviewer issues in wave 2 (Finn & Ranchhod, 2017). In wave 1, Coloured or Asian/Indian individuals have a lower probability of being employed, compared to White individuals, and this is significant at the 10% and 1% level respectively. Individuals residing in the Western Cape in wave 1 had a higher probability of being employed, compared to individuals in other provinces.

Although there are several explanatory variables included in the above regression models, which is atypical of a dataset that contains a small sample size, these variables are in line with those used by both Morris (2007) and Some, Rashied and Ohonba (2016). The correlation matrices shown in Table 9 (wave 1) and Table 10 (wave 2) show that these variables are not highly correlated, so issues of multicollinearity are unlikely, and as such all add explanatory power to the models.

In summary, the results in the bivariate probit models show that there is no interdependence between obesity and employment status using the sample. Being female, being in a relationship and log of household income positively impact the probability of being obese in both waves, whereas being female, household size and log of household income all positively impact the probability of being employed in both waves. The results of the recursive bivariate models show that the null hypothesis of exogeneity cannot be rejected, indicating that obesity and employment status are independent of one another.

**Table 8: Selected Recursive Bivariate Probit estimation results for wave 1 and wave 2 (second stage)**

	Wave 1		Wave 2	
	Recursive Bivariate Probit		Recursive Bivariate Probit	
	Coef.	Sig.	Coef.	Sig.
<b>Broad Employment</b>				
Obese	0.014		0.098	
Age	0.038		0.106	***
Age squared	0.000		0.001	***
Gender	-0.555	***	0.285	
<b>Race</b>				
Coloured	-0.495	*	0.352	
Asian/Indian	-1.326	***	1.128	**
White	-0.261		0.025	
Settlement	0.039		0.183	*
Relationship status	-0.067		0.193	*
<b>Province</b>				
Eastern Cape	-0.484	**	0.059	
Northern Cape	-0.688	***	0.039	
Free State	-1.229	***	0.020	
KwaZulu-Natal	-0.508	*	0.065	
North West	-0.967	***	0.050	
Gauteng	-0.916	***	0.027	
Mpumalanga	-0.968	***	0.129	
Limpopo	-0.935	***	0.102	
Education	-0.015		0.019	
Household size	-0.108	***	0.117	***
Log household income	0.715	***	0.590	***
<b>Home language</b>				
IsiXhosa	-0.324		0.285	
IsiNdebele	0.169		-0.038	
Sepedi	0.065		0.026	
Sesotho	0.125		-0.134	
Setswana	0.085		-0.056	
SiSwati	0.551	*	-0.162	
Tshivenda	0.479		0.041	
IsiTonga	0.361		0.184	
Afrikaans	-0.122		0.253	
English	0.271		0.909	**
<b>Emotional wellbeing</b>				
Good / Very good	0.003		0.229	
Excellent	-0.082		0.167	
<b>Physical health</b>				
Physical health	0.089		0.130	
<b>Mental health</b>				
Often Depressed	-0.156		0.737	
Occasionally depressed	-0.040		0.643	
Not depressed	-0.664		0.723	
<hr/>				
Observations	2850		2850	
Pseudo $R^2$	0.0215		0.0882	
Rho ( $\rho$ )	0.0215		0.0880	
Wald test $\rho = 0$	$\chi^2(1) = 0.0566$		$\chi^2(1) = 0.0456$	
(p-value)	[0.9400]		[0.8310]	

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Reference categories for categorical variables: Gender (Male); Race (African); Settlement (Rural); Relationship (Single); Province (Western Cape); Home language (IsiZulu); Emotional wellbeing (Poor); Physical health (Poor); Mental health (Always depressed)

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table 9: Correlation matrix for explanatory variables in wave 1**

	Age	Age squared	Gender	Race	Settlement	Relationship status	Province	Education	Household size	Log household income	Home language	Emotional wellbeing	Physical health	Mental health
Age	1.00													
Age squared	0.99	1.00												
Gender	0.02	0.01	1.00											
Race	0.11	0.11	-0.01	1.00										
Settlement	0.07	0.07	0.02	0.21	1.00									
Relationship status	0.38	0.35	-0.07	0.14	0.08	1.00								
Province	0.00	0.00	-0.02	-0.33	-0.16	-0.01	1.00							
Education	0.32	-0.33	0.03	0.14	0.19	-0.12	0.05	1.00						
Household size	-	-	-	-	-	-	-	-	1.00					
Log household income	0.17	-0.15	0.15	-0.07	-0.15	-0.08	0.01	-0.02	0.18	1.00				
Home language	0.10	0.09	0.00	0.37	0.26	0.17	0.00	0.37	0.18	0.29	1.00			
Emotional wellbeing	0.06	0.05	-0.04	0.67	0.26	0.16	-0.25	0.07	-0.09	0.29	0.03	1.00		
Physical health	0.28	-0.28	-0.11	0.02	0.01	-0.06	0.01	0.22	0.00	0.06	0.03	0.12	1.00	
Mental health	0.17	-0.17	-0.23	0.10	0.05	-0.10	0.01	0.19	-0.04	0.08	0.12	0.12	0.12	1.00
	0.04	-0.04	-0.08	0.13	0.05	0.04	-0.06	0.11	0.01	0.16	0.07	0.17	0.05	0.05

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table 10:** Correlation matrix for explanatory variables in wave 2

	Age	Age squared	Gender	Race	Settlement	Relationship status	Province	Education	Household size	Log household income	Home language	Emotional wellbeing	Physical health	Mental health
Age	1.00													
Age squared	0.99	1.00												
Gender	0.02	0.01	1.00											
Race	0.11	0.11	-0.01	1.00										
Settlement	0.05	0.05	0.00	0.21	1.00									
Relationship status	0.37	0.34	-0.07	0.15	0.09	1.00								
Province	0.01	0.00	-0.02	-0.33	-0.16	-0.02	1.00							
Education	0.32	-0.33	0.04	0.13	0.20	-0.09	0.05	1.00						
Household size	0.14	-0.13	0.17	-0.08	-0.18	-0.08	0.00	-0.06	1.00					
Log household income	0.10	0.10	-0.01	0.31	0.19	0.17	0.01	0.36	0.15	1.00				
Home language	0.06	0.06	-0.05	0.67	0.26	0.15	-0.25	0.06	-0.12	0.18	1.00			
Emotional wellbeing	0.24	-0.24	-0.09	0.04	0.03	-0.08	0.00	0.17	0.03	0.06	0.07	1.00		
Physical health	0.12	-0.12	-0.18	0.06	0.07	-0.03	0.02	0.16	-0.05	0.08	0.00	0.09	1.00	
Mental health	0.05	-0.04	-0.07	0.15	0.04	0.03	-0.07	0.11	0.02	0.09	0.19	0.18	0.07	1.00

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

### *Univariate Probit Model*

Table 11 below reports selected results from the univariate probit estimation and the associated marginal effects. Given that the transition from not obese and employed to obese and unemployed demonstrated some of the highest variation in the transition matrix in Table 5, the outcome variable is a binary variable for whether individual transitioned from non-obese to obese over the two time periods or not. Employment status is broadened to include individuals classified as not economically active, to analyse the impact a change in labour market state has on transition into or out of obesity across the two waves in more granularity.

The explanatory power of the univariate probit model is tested using the Hosmer-Lemeshow goodness-of-fit test. The p-value of the test statistic is just greater than 0.1 ( $0.1020 > 0.1$ ) and as such the null hypothesis that the model is a good fit for the data cannot be rejected. The results of the univariate probit estimation show that transitions in labour market states do not have a significant impact on the probability of transitioning from not obese in wave 1 to obese in wave 2, however, it is seen that transitions out of employment (to either unemployed or not economically active) and transitioning from unemployed to not economically active decrease the probability of transitioning to obese.

The change in labour market state variable indicates that, holding all else equal, a transition from not economically active to employed over the two-year period increases the probability of becoming obese by 2.9%, compared to individuals who do no change labour market states, with this result being significant at the 10% level. However, the lack of statistically significant results for other changes in labour market states suggests that there may be factors other than changes in labour market status, that lead to significant changes in weight status. Gender, age (as a parabolic relationship), race, education, relationship status, education, relationship status, province and self-perceived emotional wellbeing all appear to have a statistically significant influence on the probability of transitioning from non-obese in wave 1 to obese in wave 2.

The marginal effects reported in Table 11 show that females are 4.18% more likely to transition from non-obese to obese over a two-year period, compared to males holding all else equal with this result being significant at the 1% level. Age is shown to have a significant (1% level) inverted U-shape relationship with the probability of transitioning to obesity. The probability increases up until age 42<sup>8</sup>, where thereafter, the probability of transitioning from non-obese to obese decreases. In addition, an additional year of education, being in a committed relationship and residing outside of the Western Cape (bar the Northern Cape) are all factors which significantly increase the probability of transitioning from non-obese in wave 1 to obese in wave 2 (although by minor magnitudes). Finally, individuals with self-perceived good or excellent emotional wellbeing are 2.92% and 3.5% more likely to transition from non-obese to obese over the two-year period, compared to individuals who perceive themselves to have poor emotional wellbeing, *ceteris paribus*, with these results being significant at the 1% level. Given that different demographic groups have varying beliefs as to what a “normal” weight is, it is not

---

<sup>8</sup>  $41.85 = (-0.0052488) / 2(-0.0000627)$

unusual that good emotional wellbeing influences weight status (Kilicarslan *et al*, 2006; Joubert *et al*, 2007; Rosin, 2008).

**Table 11:** Selected univariate probit coefficient and marginal effects results

	Coef.	Sig.	dy/dx	Sig.
<b>Transitioned to Obese</b>				
<b>Labour Market State Transition</b>				
Transition from NEA to Unemployed	0.014		0.002	
Transition from NEA to Employed	0.159	*	0.029	*
Transition from Unemployed to NEA	-0.020		-0.003	
Transition from Unemployed to Employed	0.029		0.005	
Transition from Employed to NEA	-0.060		-0.010	
Transition from Employed to Unemployed	-0.085		-0.013	
Gender	0.252	***	0.042	***
Age	0.032	***	0.005	***
Age squared	-0.000	***	-0.000	***
<b>Race</b>				
Coloured	0.151		0.028	
Asian/Indian	-1.739	***	-0.099	***
White	0.024		0.004	
Settlement	-0.024		-0.004	
Education	0.020	***	0.003	***
Log household income	0.029		0.005	
Relationship status	0.186	***	0.031	***
<b>Province</b>				
Eastern Cape	0.527	***	0.085	***
Northern Cape	-0.103		-0.011	
Free State	0.197		0.025	
KwaZulu-Natal	0.507	***	0.081	***
North West	0.006		0.001	
Gauteng	0.123		0.015	
Mpumalanga	0.397	**	0.059	***
Limpopo	0.408	**	0.061	**
Household size	0.005		0.001	
<b>Home language</b>				
IsiXhosa	-0.110		-0.018	
IsiZulu	0.116		0.022	
Sepedi	-0.152		-0.024	
Sesotho	-0.045		-0.008	
Setswana	0.173		0.034	
SiSwati	-0.254	*	-0.038	**
Tshivenda	0.102		0.019	
IsiTonga	-0.281	**	-0.042	**
Afrikaans	-0.108		-0.018	
English	-0.034		-0.006	
<b>Emotional wellbeing</b>				
Good / Very good	0.197	**	0.029	***
Excellent	0.230	***	0.035	***
<b>Physical health</b>				
Physical health	0.012		0.002	
<b>Mental health</b>				
Often Depressed	-0.034		-0.006	
Occasionally depressed	-0.094		-0.016	
Not depressed	-0.205		-0.033	
Constant	-2.900	*		
Observations		14427		
Pseudo $R^2$		0.0461		
Wald test $\rho = 0$		$\chi^2(41) = 261.150$		
(p-value)		(0.0000)		

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Reference categories for categorical variables: Labour Market State (no change in state); Gender (Male); Race (African); Settlement (Rural); Relationship (Single); Province (Western Cape); Home language (IsiZulu); Emotional wellbeing (Poor); Physical health (Poor); Mental health (Always depressed)

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

## 5. Discussion and limitations

This study utilises waves 1 and 2 of NIDS, given the possible exacerbated impacts on weight status and employment status as a result of the 2009 recession in SA, to assess whether a significant bivariate relationship and endogeneity are present when estimating the impact of obesity on employment, in the SA labour market. As a next step, wave 4 (finalised in 2014) and wave 5 (finalised in 2017) of NIDS should be used to assess whether exogeneity still exists in more recent years. However, given the endemic nature of obesity in SA, it is likely that obesity affects the entire distribution of employed and unemployed individuals, and as such the results are unlikely to change. Additionally, a panel dataset utilising all five waves of NIDS could be used to assess how changes in employment status affect fluctuations in weight status over several time periods.

Notwithstanding the range of limitations discussed below, the study identified that obesity and employment status are independent of one another in the recursive bivariate probit model. Previous literature finds that obesity is influenced by lifestyle and spending habits, nutrition, and economic resources (Rush & Yan, 2017; Chooi, Ding and Magkos, 2019; Gearhardt & Hebebrand, 2021). The results from the univariate probit model indicate that transitions in labour market status, other than transitioning from not economically active to employed, do not have significant explanatory power in predicting the probability of becoming, and several other lifestyle variables hypothesised to explain transitions in weight status such as home language as a proxy for ethnolinguistic characteristics, mental and physical health are all shown to be insignificant. These results suggest that nutrition and spending habits associated with food could have a more weighted impact on fluctuations in weight status compared to factors such as lifestyle and economic resources. However, the lack of variables measuring food quality intake, genetic composition, metabolic rate, and measurements which take into consideration an individual's total body fat compositions, body fat percentage, fatness and fat-free mass within the NIDS dataset make it impossible to confirm this.

A limitation of this study is thus the inability to identify whether nutrition impacts obesity in SA using the NIDS dataset, as the dataset does not have measures which reflect the nutritional value of the food consumed by respondents. Although obesity is a multifaceted disease with no single cause, nutrition plays a significant role in determining an individual's propensity for obesity (Rush & Yan, 2017). Given that this analysis shows no issue of dependence or endogeneity between obesity and employment, it is likely that obesity is far more endemic and other factors such as malnutrition due to poverty or overeating due to lifestyle habits may be stronger underlying causes of the diseases. This motivates further investigation into the dietary composition of the food consumed by individuals in SA. As such, an extension of this investigation would be to examine whether nutritional factors and intake significantly impact the probability of transitioning to obese, using alternative weight measurements which take into consideration an individual's total body fat compositions, body fat percentage, fatness, and fat-free mass to distinguish obese individuals more accurately from non-obese individuals.

The Wald test results of independence between obesity and employment in the bivariate probit models, and exogeneity of obesity when included as a binary explanatory variable in the estimation of employment propensity using recursive bivariate probit models are different from the results of Morris

(2007), Some, Rashied and Ohonba (2016) and Henry and Kollamparambil (2017). A possible explanation for this is that both Morris (2007) and Some, Rashied and Ohonba (2016) implement instrumental variables for obesity in their bivariate probit models to analyse the impact of obesity on employment status. The insignificant rho in both the bivariate and the recursive bivariate probit model results could also be attributable to the interviewer error that occurred with the NIDS wave 2 data (Finn & Ranchhod, 2017).

However, the objective of this study was to identify whether endogeneity existed using a recursive bivariate probit model for two binary variables. While Morris (2007), Some, Rashied and Ohonba (2016) and Henry and Kollamparambil (2017) all find endogeneity present in their univariate probit models, this is not the case for the univariate probit model in this investigation, although the univariate probit model in this study uses panel data. This approach is recommended by Some, Rashied and Ohonba (2016) as a means of providing more robust results that better account for unobserved factors. One caveat to using a panel dataset to identify treatment dynamics is that changes in treatment could be driven by measurement error. Measurement error can occur when choosing a discrete point in BMI as a cut-off value, such as 30 kg/m<sup>2</sup>, as a discrete point could be mismeasured, which would lead to the results being insignificant. Further, both Burkhauser and Cawley (2007) and Henry and Kollamparambil (2017) critique existing BMI cut-off values as inaccurate measures of obesity across different population groups.

The univariate probit results show that transitioning between different labour market states (against a base case of no change in state) does not have a causal impact on the transition from non-obese to obese, apart from transitioning from not economically active to employed, which has a significant and positive impact on the probability of transitioning to obese. Further, the log of household income, as a proxy for the ability to afford nutritional, quality food, shows to have a significant and positive impact on the probability of being obese. A possible explanation for these two results is that the more income an individual receives, either subsequent to gaining employment or receiving increases in wages or salary, the more disposable income they have to direct towards purchasing of food such as fast foods.

In the sample, the descriptive statistics show how obesity, particularly amongst women, continues to be an issue in SA, with policy interventions having limited impact- approximately 40% of females in the sample across both waves are obese, and in 2016, 41% of the female population continued to be classified as obese (NDoH, 2019). However, a further limitation of this study was the sample size of individuals who had non-missing data for the variables of interest. This prevented performing separate analyses for males and females for the bivariate and recursive bivariate probit models. Given that the results show that females have a statistically significant higher probability of becoming both obese and unemployed compared to males, a more nuanced approach which performs separate models for males and females would be valuable in understanding the magnitude of these effects, as well as age-related trends.

## 6. Conclusion

This study had three main aims. The first was to assess whether a simultaneous relationship exists between employment status and obesity status in the context of the South African labour market using a bivariate probit model for each wave of the NIDS data. The second was to investigate if obesity status is an endogenous regressor in the model estimating the impact on probability of gaining employment using a recursive bivariate probit model. Once again this was performed using cross-sectional data for each wave. The third was to understand the direction and significance that changes in labour market state had on the probability of transitioning from non-obese to obese over a two-year period, on condition that obesity and employment are independent. This required the use of panel data for the two waves.

Using wave 1 and wave 2 NIDS data, the results of this analysis show firstly, that the error terms between employment status and obesity status in the bivariate probit model are unrelated, and hence there is no issue of simultaneity between two variables, nor are they jointly determined. Secondly, the recursive bivariate probit model results show that the binary obesity variable is not an endogenous regressor in the equation where the binary employment status variable is the dependent variable. This result confirms the first, suggesting that the recursive bivariate probit model does not have superior explanatory power compared to two separate univariate probit models. Thirdly, a univariate probit model shows to be a good fit for the panel data used in this analysis. The second result provides the motivation for implementing this model.

The results of the univariate probit model suggest that changes in labour market state, other than transitioning from not economically active to employed, do not significantly impact the probability of transitioning into obesity over a two-year period. However, gender plays a significant role in determining the probability of becoming both unemployed and obese. This study contributes to existing literature on obesity and employment by conducting these specific investigations using the particular models described in the South African context. The study finds that obesity and employment status are independent using in the bivariate probit models and endogeneity is not statistically significant in the recursive bivariate probit models.

Across all three models, females have a higher probability of becoming unemployed and obese in a single time period, as well as transitioning into obesity over a two-year period, compared to men. This suggests the urgent need for more nuanced and gender-specific policy measures to be taken to better address both the obesity and unemployment crisis in SA. Additionally, the inability to observe both malnutrition-led and overeating-led obesity due to the limitations of the NIDS dataset as regards measuring nutritional in-take. Burkhauser and Cawley (2007) argue that more fatness measures should be included in social science datasets based on biomedical literature findings that BMI does not accurately distinguish adipose tissue from fat-free mass (bones and muscles).

The independence of obesity and employment status and no observed endogeneity in the study suggests that there are other underlying factors which impact changes in weight status and employment status. However, potential fabrications that occurred when wave 2 was being compiled may have

adversely impacted the sample size of this study. Given the interviewer error in wave 2, it is possible that measurement error is driving the lack of significance between obesity and unemployment status. As such a potential extension of this study is to use more recent waves of NIDS to conduct this research question in an attempt of establishing a larger sample size. Further, the univariate probit results suggest that factors other than changes in labour market state impact changes in weight status and is motivation for further investigation on how nutritional diversity and calorific intensity of food consumed by individuals influences the prevalence of obesity in SA.

## 7. References

- Abegunde, D.O., Mathers, C.D., Adam, T., Ortegón, M. and Strong, K., 2007. The burden and costs of chronic diseases in low-income and middle-income countries. *The Lancet*, 370(9603), pp.1929-1938.
- Adeniyi, O.V., Longo-Mbenza, B. and Ter Goon, D., 2015. Female sex, poverty and globalization as determinants of obesity among rural South African type 2 diabetics: a cross-sectional study. *BMC public health*, 15(1), p.298.
- Alaba, O. and Chola, L., 2014. Socioeconomic inequalities in adult obesity prevalence in South Africa: a decomposition analysis. *International journal of environmental research and public health*, 11(3), pp.3387-3406.
- Andreyeva, T., Luedicke, J. and Wang, Y.C., 2014. State-level estimates of obesity-attributable costs of absenteeism. *Journal of occupational and environmental medicine/American College of Occupational and Environmental Medicine*, 56(11), p.1120.
- Ardington, C. and Gasealahwe, B., 2012. Health: analysis of the NIDS wave 1 and 2 datasets. University of Cape Town. Available: <http://www.caps.uct.ac.za/handle/11090/173> [2020, January 24].
- Avila, C., Holloway, A.C., Hahn, M.K., Morrison, K.M., Restivo, M., Anglin, R. and Taylor, V.H., 2015. An overview of links between obesity and mental health. *Current obesity reports*, 4(3), pp.303-310.
- Bartolucci, F., Belotti, F. and Peracchi, F., 2015. Testing for time-invariant unobserved heterogeneity in generalized linear models for panel data. *Journal of Econometrics*, 184(1), pp.111-123.
- Bennett, K.J., Probst, J.C. and Pumkam, C., 2011. Obesity among working age adults: the role of county-level persistent poverty in rural disparities. *Health & place*, 17(5), pp.1174-1181.
- Bhorat, H. and Goga, S., 2013. The gender wage gap in post-apartheid South Africa: A re-examination. *Journal of African Economies*, 22(5), pp.827-848.
- Boutayeb, A. and Boutayeb, S., 2005. The burden of non communicable diseases in developing countries. *International journal for equity in health*, 4(1), p.2.
- Burkhauser, R.V. and Cawley, J., 2008. Beyond BMI: the value of more accurate measures of fatness and obesity in social science research. *Journal of health economics*, 27(2), pp.519-529.
- Cawley, J., 2004. The impact of obesity on wages. *Journal of Human resources*, 39(2), pp.451-474.
- Chooi, Y.C., Ding, C. and Magkos, F., 2019. The epidemiology of obesity. *Metabolism*, 92, pp.6-10.
- Cois, A. and Day, C., 2015. Obesity trends and risk factors in the South African adult population. *BMC obesity*, 2(1), p.42.
- De Sousa, S., 2012. Does size matter? A propensity score approach to the effect of BMI on labour market outcomes. *EUI Florence*.
- De Onis, M. and Blössner, M., 2003. The World Health Organization global database on child growth and malnutrition: methodology and applications. *International journal of epidemiology*, 32(4), pp.518-526.
- Dogbe, W., 2020. Can poverty status explain obesity in developing countries? Evidence from Ghana. *Agribusiness*.
- Dowdall, N., Ward, C.L. and Lund, C., 2017. The association between neighbourhood-level deprivation and depression: evidence from the South African national income dynamics study. *BMC psychiatry*, 17(1), pp.1-10.
- Drewnowski, A. and Specter, S.E., 2004. Poverty and obesity: the role of energy density and energy costs. *The American journal of clinical nutrition*, 79(1), pp.6-16.
- Filippini, M., Greene, W.H., Kumar, N. and Martinez-Cruz, A.L., 2018. A note on the different interpretation of the correlation parameters in the Bivariate Probit and the Recursive Bivariate Probit. *Economics Letters*, 167, pp.104-107.
- Finn, A. and Ranchhod, V., 2017. Genuine fakes: The prevalence and implications of data fabrication in a large South African survey. *The World Bank Economic Review*, 31(1), pp.129-157.

Flegal, K.M., Kit, B.K., Orpana, H. and Graubard, B.I., 2013. Association of all-cause mortality with overweight and obesity using standard body mass index categories: a systematic review and meta-analysis. *Jama*, 309(1), pp.71-82.

Freedman, D.S., 2011. Obesity—United States, 1988–2008. Centers for Disease Control and Prevention (CDC), *MMWR Surveill Summ*, 60(01), pp.73-7.

Gearhardt, A.N. and Hebebrand, J., 2021. The concept of “food addiction” helps inform the understanding of overeating and obesity: Debate Consensus. *The American Journal of Clinical Nutrition*.

Goldsmith, A.H., Veum, J.R. and Darity Jr, W., 1996. The psychological impact of unemployment and joblessness. *The journal of socio-economics*, 25(3), pp.333-358.

Gortmaker, S.L., Swinburn, B.A., Levy, D., Carter, R., Mabry, P.L., Finegood, D.T., Huang, T., Marsh, T. and Moodie, M.L., 2011. Changing the future of obesity: science, policy, and action. *The Lancet*, 378(9793), pp.838-847.

Greene, W.H., 2003. *Econometric analysis (5th edition)*. Pearson Education, Inc., Upper Saddle River, New Jersey, 07458.

Greene, W., 2004. Convenient estimators for the panel probit model: Further results. *Empirical Economics*, 29(1), pp.21-47.

Hales CM, Carroll MD, Fryar CD, Ogden CL. 2020. *Prevalence of obesity and severe obesity among adults: United States, 2017–2018*. NCHS Data Brief, no 360. Hyattsville, MD: National Center for Health Statistics.

Henry, J. and Kollamparambil, U., 2017. Obesity-based labour market discrimination in South Africa: a dynamic panel analysis. *Journal of Public Health*, 25(6), pp.671-684.

Hergenrather, K.C., Zeglin, R.J., McGuire-Kuletz, M. and Rhodes, S.D., 2015. Employment as a social determinant of health: a systematic review of longitudinal studies exploring the relationship between employment status and physical health. *Rehabilitation Research, Policy, and Education*, 29(1), pp.2-26.

Joubert, J., Norman, R., Bradshaw, D., Goedecke, J.H., Steyn, N.P. and Puoane, T., 2007. Estimating the burden of disease attributable to excess body weight in South Africa in 2000. *South African Medical Journal*, 97(8), pp.683-690.

Kilicarslan, A., Isildak, M., Guven, G.S., Oz, S.G., Tannover, M.D., Duman, A.E., Saracbası, O. and Sozen, T., 2006. Demographic, socioeconomic and educational aspects of obesity in an adult population. *Journal of the National Medical Association*, 98(8), p.1313.

Kingdon, G. and Knight, J., 2001. What have we learnt about unemployment from microdatasets in South Africa?. *Social dynamics*, 27(1), pp.79-95.

Kjellberg, J., Larsen, A.T., Ibsen, R. and Højgaard, B., 2017. The socioeconomic burden of obesity. *Obesity facts*, 10(5), pp.493-502.

Kortt, M.A., Langley, P.C. and Cox, E.R., 1998. A review of cost-of-illness studies on obesity. *Clinical therapeutics*, 20(4), pp.772-779.

Kruger, H.S., Puoane, T., Senekal, M. and Van Der Merwe, M.T., 2005. Obesity in South Africa: challenges for government and health professionals. *Public health nutrition*, 8(5), pp.491-500.

Laitinen, J., Power, C., Ek, E., Sovio, U. and Järvelin, M.R., 2002. Unemployment and obesity among young adults in a northern Finland 1966 birth cohort. *International journal of obesity*, 26(10), p.1329.

Lal, A., Moodie, M., Ashton, T., Siahpush, M. and Swinburn, B., 2012. Health care and lost productivity costs of overweight and obesity in New Zealand. *Australian and New Zealand journal of public health*, 36(6), pp.550-556.

Lau, Y.K., Tam, J., Fleischer, N.L. and Meza, R., 2018. Neighbourhood deprivation, smoking, and race in South Africa: a cross-sectional analysis. *Preventive medicine reports*, 11, pp.202-208.

Lehnert, T., Sonntag, D., Konnopka, A., Riedel-Heller, S. and König, H.H., 2013. Economic costs of overweight and obesity. *Best practice & research Clinical endocrinology & metabolism*, 27(2), pp.105-115.

- Li, C., Poskitt, D.S. and Zhao, X., 2019. The bivariate probit model, maximum likelihood estimation, pseudo true parameters and partial identification. *Journal of Econometrics*, 209(1), pp.94-113.
- Lindeboom, M., Lundborg, P. and Van Der Klaauw, B., 2010. Assessing the impact of obesity on labor market outcomes. *Economics & Human Biology*, 8(3), pp.309-319.
- Lopez, A.D. and Murray, C.C., 1998. The global burden of disease, 1990–2020. *Nature medicine*, 4(11), pp.1241-1243.
- Maddala, G. S., 1983. Limited-dependent and qualitative variables in econometrics, 3, Cambridge, UK: Cambridge University Press.
- Mchiza, Z.J.R., Parker, W.A., Sewpaul, R., Onagbiye, S.O. and Labadarios, D., 2020. Body image and the double burden of nutrition among South Africans from diverse sociodemographic backgrounds: SANHANES-1. *International journal of environmental research and public health*, 17(3), p.887.
- McKee-Ryan, F., Song, Z., Wanberg, C.R. and Kinicki, A.J., 2005. Psychological and physical well-being during unemployment: a meta-analytic study. *Journal of applied psychology*, 90(1), p.53.
- Micklesfield, L.K., Lambert, E.V., Hume, D.J., Chantler, S., Pienaar, P.R., Dickie, K., Goedecke, J.H. and Puoane, T., 2013. Socio-cultural, environmental and behavioural determinants of obesity in black South African women. *Cardiovascular journal of Africa*, 24(9), p.369.
- Monteiro, C.A., Moura, E.C., Conde, W.L. and Popkin, B.M., 2004. Socioeconomic status and obesity in adult populations of developing countries: a review. *Bulletin of the World Health Organization*, 82, pp.940-946.
- Morris, S., 2007. The impact of obesity on employment. *Labour Economics*, 14(3), pp.413-433.
- Mthembu, S. and Eyal, K., 2018. Nurture surpasses nature: The intergenerational transmission of depression from African mothers to their adolescent children.
- National Department of Health (NDoH), Statistics South Africa (Stats SA), South African Medical Research Council (SAMRC), and ICF. 2019. South Africa Demographic and Health Survey 2016. Pretoria, South Africa, and Rockville, Maryland, USA: NDoH, Stats SA, SAMRC, and ICF.
- Ng, M., Fleming, T., Robinson, M., Thomson, B., Graetz, N., Margono, C., Mullany, E.C., Biryukov, S., Abbafati, C., Abera, S.F. and Abraham, J.P., 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), pp.766-781.
- Nojilana, B., Bradshaw, D., Pillay-van Wyk, V., Msemburi, W., Laubscher, R., Somdyala, N.I., Joubert, J.D., Groenewald, P. and Dorrington, R.E., 2016. Emerging trends in non-communicable disease mortality in South Africa, 1997-2010. *South African medical journal*, 106(5), pp.477-484.
- Norton, E.C. and Han, E., 2008. Genetic information, obesity, and labor market outcomes. *Health economics*, 17(9), pp.1089-1104.
- Ntuk, U.E., Gill, J.M., Mackay, D.F., Sattar, N. and Pell, J.P., 2014. Ethnic-specific obesity cutoffs for diabetes risk: cross-sectional study of 490,288 UK biobank participants. *Diabetes care*, 37(9), pp.2500-2507.
- Ogden, C.L., Yanovski, S.Z., Carroll, M.D. and Flegal, K.M., 2007. The epidemiology of obesity. *Gastroenterology*, 132(6), pp.2087-2102.
- Otterbach, S., Oskorouchi, H.R., Rogan, M. and Qaim, M., 2021. Using Google data to measure the role of Big Food and fast food in South Africa's obesity epidemic. *World Development*, 140, p.105368.
- Pacheco, G., Page, D. and Webber, D.J., 2014. Mental and physical health: re-assessing the relationship with employment propensity. *Work, employment and society*, 28(3), pp.407-429.
- Paraponaris, A., Saliba, B. and Ventelou, B., 2005. Obesity, weight status and employability: empirical evidence from a French national survey. *Economics & Human Biology*, 3(2), pp.241-258.
- Parliamentary Monitoring Group. 2009. *South Africa's Response to the Global Economic Crisis: Ministerial briefing*. Available: <https://pmg.org.za/committee-meeting/10717/> [2022, January 12]

Phetla, M.C. and Skaal, L., 2017. Perceptions of healthcare professionals regarding their own body weight in selected public hospitals in Mpumalanga Province, South Africa. *South African Medical Journal*, 107(4), pp.338-341.

Pienaar, A.E., 2015. Prevalence of overweight and obesity among primary school children in a developing country: NW-CHILD longitudinal data of 6–9-yr-old children in South Africa. *BMC obesity*, 2(1), p.2.

Radloff, L.S., 1977. The CES-D scale: A self-report depression scale for research in the general population. *Applied psychological measurement*, 1(3), pp.385-401.

Rahman, M. and Berenson, A.B., 2010. Accuracy of current body mass index obesity classification for white, black and Hispanic reproductive-age women. *Obstetrics and gynecology*, 115(5), p.982.

Rayton, B.A., 2006. Examining the interconnection of job satisfaction and organizational commitment: An application of the bivariate probit model. *The International Journal of Human Resource Management*, 17(1), pp.139-154.

Rosin, O., 2008. The economic causes of obesity: a survey. *Journal of Economic Surveys*, 22(4), pp.617-647.

Rush, E.C. and Yan, M.R., 2017. Evolution not revolution: nutrition and obesity. *Nutrients*, 9(5), p.519.

Sarlio-Lähteenkorva, S. and Lahelma, E., 1999. The association of body mass index with social and economic disadvantage in women and men. *International journal of epidemiology*, 28(3), pp.445-449.

Seidell, J.C., 1998. Societal and personal costs of obesity. *Experimental and clinical endocrinology & diabetes*, 106(S 02), pp.7-10.

Senekal, M., Steyn, N.P. and Nel, J.H., 2003. Factors associated with overweight/obesity in economically active South African populations. *Ethnicity & disease*, 13(1), pp.109-116.

Shekar, M. and Popkin, B., 2020. *Obesity: health and economic consequences of an impending global challenge*. World Bank Publications.

Some, M., Rashied, N. and Ohonba, A., 2016. The impact of obesity on employment in South Africa. *Studies in Economics and Econometrics*, 40(2), pp.87-104.

Southern Africa Labour and Development Research Unit. National Income Dynamics Study (NIDS) Wave 1, 2008 [dataset]. Version 7.0.0. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. <https://doi.org/10.25828/e7w9-m033>

Southern Africa Labour and Development Research Unit. National Income Dynamics Study Wave 2, 2010-2011 [dataset]. Version 4.0.0. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. <https://doi.org/10.25828/j1h1-5m16>

Statistics South Africa. 2018. Mortality and causes of deaths in South Africa, 2016: Findings from death notification. Available: <http://www.statssa.gov.za/publications/P03093/P030932016.pdf> [2019, September 20].

Statistics South Africa. 2021. *Consumer Price Index (CPI), December 2020*. (Research report P0141). Available: <http://www.statssa.gov.za/publications/P0141/CPIHistory.pdf> [2021, January 21].

Stevens, J., McClain, J.E. and Truesdale, K.P., 2008. Selection of measures in epidemiologic studies of the consequences of obesity. *International Journal of Obesity*, 32(3), pp.S60-S66.

Sturm, R., An, R., Maroba, J. and Patel, D., 2013. The effects of obesity, smoking, and excessive alcohol intake on healthcare expenditure in a comprehensive medical scheme. *South African Medical Journal*, 103(11), pp.840-844.

Tathiah, N., Moodley, I., Mubaiwa, V., Denny, L. and Taylor, M., 2013. South Africa's nutritional transition: Overweight, obesity, underweight and stunting in female primary school learners in rural KwaZulu-Natal, South Africa. *South African Medical Journal*, 103(10), pp.718-722.

Tremmel, M., Gerdtham, U.G., Nilsson, P.M. and Saha, S., 2017. Economic burden of obesity: a systematic literature review. *International journal of environmental research and public health*, 14(4), p.435.

Tugendhaft, A., Manyema, M., Veerman, L.J., Chola, L., Labadarios, D. and Hofman, K.J., 2016. Cost of inaction on sugar-sweetened beverage consumption: implications for obesity in South Africa. *Public health nutrition*, 19(13), pp.2296-2304.

van der Noordt, M., IJzelenberg, H., Droomers, M. and Proper, K.I., 2014. Health effects of employment: a systematic review of prospective studies. *Occupational and environmental medicine*, 71(10), pp.730-736.

Wang, Y.C., McPherson, K., Marsh, T., Gortmaker, S.L. and Brown, M., 2011. Health and economic burden of the projected obesity trends in the USA and the UK. *The Lancet*, 378(9793), pp.815-825.

Wittenberg, M., 2011. The weight of success: The body mass index and economic well-being in South Africa.

Wilde, J., 2000. Identification of multiple equation probit models with endogenous dummy regressors. *Economics letters*, 69(3), pp.309-312.

World Health Organization, 1998. *Obesity: preventing and managing the global epidemic: report of a WHO consultation on obesity, Geneva, 3-5 June 1997* (No. WHO/NUT/NCD/98.1). Geneva: World Health Organization.

World Health Organization. 2020. *Obesity and overweight*. Available: <https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight> [2021, January 27].

World Health Organization. 2021. *BMI for age (5-19 years)*. Available: <https://www.who.int/tools/growth-reference-data-for-5to19-years/indicators/bmi-for-age> [2021, January 14].

World Obesity. 2021. *Prevalence of obesity*. Available: <https://www.worldobesity.org/about/about-obesity/prevalence-of-obesity> [2021, January 27].

## I. Appendix

### IA. Key literature findings

**Table A.1:** *Studies on weight status and labour market outcomes*

Author(s); Year	Research Question	Analytical Methodology	Results	Principal Findings
Cawley (2004)	Explore whether (i) obesity lowering wages; (ii) low wages causing obesity, or (iii) unobserved factors causing both obesity and low wages is responsible for the correlation between BMI (weight) and wages in America	OLS; IV estimations using (i) correlated variables, and (ii) lagged values of BMI; Fixed effects (first differencing)	<p>The OLS results using BMI as an explanatory variable and OLS results using lagged BMI (to avoid the influence of wages on contemporaneous weight) as an explanatory variable reflect a negative relationship between weight and wages for white, Hispanic and black females, as well as Hispanic males. However, a positive relationship was observed for black males.</p> <p>Fixed effects to account for the influence of time-variant unobserved heterogeneity results in only white females demonstrating a negative relationship between weight and wages.</p> <p>The remaining IV estimation results show that weight has a significant negative impact on wages for white females only.</p>	<p>The results across OLS Fixed effects and IV are only consistent for white females, whereas the negative correlation between increases in BMI and wages observed for black and Hispanic females and Hispanic males appear to be a result of unobserved heterogeneity.</p> <p>Further, the outlying result increasing in BMI resulting in increase in wage for black males can largely be attributed to underweight black males earning less than black males with a BMI greater than 18.5 kg/m<sup>2</sup>.</p>
De Sousa (2012)	The effect of overweight and obesity on labour market outcomes in European countries	OLS; Univariate probit estimation; Propensity score matching	A BMI above or equal to 25kg/m <sup>2</sup> has a positive and significant impact on labour force participation for men for all three models, whereas for women, there is a significant negative association for all three models.	After controlling for endogeneity using propensity score matching, the causal direction for both genders remains the same. The magnitude of the ATT <sup>ii</sup> results is larger than both the OLS and probit results for females. For males, the

Henry and Kollamparambil (2017)	Investigate the relationship between weight status and (i) employment status, and (ii) wage levels of individuals in South Africa to identify the optimal BMI level from the labour market	Linear probability model; Probit; Tobit; System GMM	All three estimations show an inverse parabolic relationship between BMI and employment probability.  The results for the three different estimations modelling the relationship between BMI and wage determination are consistent, indicating an inverted U-shaped non-linear relationship between the two variables.  The system GMM models show that a of BMI 30 kg/m <sup>2</sup> and BMI of 27 kg/m <sup>2</sup> are optimal for employment probability and wage determination, respectively.	magnitude of the ATT results is larger than the OLS, but smaller than the probit results.  The instruments used in the system GMM models for both employment probability and wage determination were valid. Endogeneity in the OLS, probit and tobit models results in an underestimation of the impact of BMI on both employment probability and wage determination. However, whilst the system GMM models account for endogeneity, there is a drop in significance levels - the linear probability models, probit and tobit models all show BMI and BMI <sup>2</sup> significant at the 1% level, whereas both the system GMM models show a significance level of only 10%.
Laitinen <i>et al</i> (2002)	Investigate if (i) obesity in adolescence (age 14) is a causal factor for sustained unemployment at age 31, and (ii) sustained periods of unemployment during adolescence increases the risk of obesity at age 31 in Finland	Longitudinal cohort analysis using binary logistic regressions	Overweight and obesity in adolescence do not predict sustained unemployment at age 31. Importantly, obesity at age 14 is shown to be a strong predictor of both adult obesity and poor educational performance.  Long periods of unemployment, defined as more than 366 days unemployed, increase the risk of obesity for females at age 31; however, sustained periods of	Whilst the authors do not take measures to test or account for endogeneity in their models, the authors conclude that obesity may indirectly impact unemployment at age 31 due to the strong association between adolescent obesity and low levels of education.

unemployment did not place males at greater risk of obesity at age 31.

Lindeboom, Lundborg and van der Klaauw (2010)

Examine the impact of obesity on labour market outcomes in Britain for individuals at ages 33 and 42

Linear probability model; IV regression; Fixed effects (first differencing)

The OLS results show a statistically significant (5% level), negative association between obesity at both ages 33 and 42 and employment for females. For males, the same association is observed, however the result is significant at the 10% level for age 33 and insignificant at age 42.

The instruments used in the IV regressions predict obesity well, however the authors raise concern over the fact that the p-values for two out the four Sargan overidentification tests are low.

The IV employment estimations show a statistically insignificant, positive relationship between employment and obesity at both ages 33 and 42 for males and females.

The tests of the instruments suggest that genetic factors are a significant contributing factor to intergenerational correlation in obesity, the validity of using parental obesity status as an instrument is brought into question given the variation in p-values for using Father's obesity status as the instrument compared to Mother's obesity status.

The first differencing estimation, which analyses the change in employment between ages 33 and 42 as a function of changes in obesity between ages 33 and 42, reflects a positive association for males which is significant at the 10% level, and an insignificant negative relationship for females.

Morris (2007)

An empirical investigation of the impact of obesity on employment in England

Univariate probit model; Propensity score matching; IV regression using a recursive bivariate probit

The univariate probit results reflect obesity has a negative, statistically significant effect on probability of employment for males, and an insignificant, positive (and small) for females.

The author fails to reject the null hypothesis of exogeneity in the univariate probit model for males, indicating that endogeneity is not an issue for the univariate model. However, the hypothesis that  $\rho = 0$  is rejected indicating that the results

In most cases, the ATT of the propensity score matching is negative and significant for

			<p>males and negative and insignificant for females. In both cases the magnitude of the ATT is larger than that of the margins in the univariate probit models.</p> <p>The results of the recursive bivariate probit models reflect a significant and negative relationship between obesity and employment for both males and females.</p>	<p>of the univariate probit model for females are biased and invalid.</p> <p>The instruments used in the recursive bivariate probit model are non-weak. When comparing the ME from the bivariate probit models to the ATT from the propensity score matching models, the order of magnitude is larger but in the same direction for males, whereas the ME is significantly more negative for females.</p>
<p>Nortan and Han (2008)</p>	<p>Analyse the impact of obesity on labour market outcomes (probability of employment and wages), using variation in genotype as an instrument to predict variation in phenotype, in America</p>	<p>Linear probability model; IV estimation using two-stage least squares</p>	<p>The linear probability models show that lagged BMI has no statistically significant explanatory power for probability of employment or wages for males. These results remain the same even after controlling for exogeneity in the 2SLS model, although the magnitude of the effect is slightly larger in the 2SLS model.</p> <p>Lagged BMI has no statistically significant explanatory power for females on labour market outcomes across all models, even after controlling for genetic information and endogeneity. However, the results of the 2SLS model for probability of employment show a more pronounced negative effect of obesity, suggesting previous literature results which did not control for endogeneity are biased.</p>	<p>The genetic instruments constructed for women predict lagged BMI well. The genetic instruments constructed for men are jointly significant but do not predict lagged BMI as well as the genetic instruments for women do. This brings into question the validity of using genetic information as an instrument to predict obesity for both males and females.</p> <p>Including sibling's BMI as an instrument improves the overall strength of the instruments for women in particular.</p>

Paraponaris, Saliba and Ventelou (2005)	Investigate (i) the impact obesity has on the ability to obtain and maintain employment, (ii) the percentage of time spent unemployment based on weight status, and (iii) the probability of regaining employment after sustained periods of unemployment in France	Logit-transformed OLS estimation; Probit estimation; Cox partial-likelihood model	Deviations from the median BMI are shown to increase both the probability of unemployment as well as percentage of working years spent unemployed. The impact of kg/m <sup>2</sup> deviations on probability of unemployment is more pronounced for females, whereas males experience a more significant change in percentage of working years spent unemployed.	The authors account for endogeneity due to the association between obesity and low socio-economic status by using the differences between the BMIs of individuals aged 20 years as a proxy for weight status.
Sarlio-Lähteenkorva and Lahelma (2005)	Evaluate the impact of weight status (BMI) on social and economic disadvantage in adult men and women in Finland	Logistic regression analysis	Overweight and obesity in women were seen to be associated with current and long-term unemployment respectively, with both results being statistically significant.  Overweight and obesity were found to have no statistically significant adverse impact on socio-economic outcomes, including employment, for men.	The authors critique the cross-sectional design of their research as a potential issue for direction of causality. The authors acknowledge that the association between obesity and low income and mobility may result in reverse causality.
Some, Rashied and Ohonba (2016)	The impact weight status has on the propensity for employment in South Africa	Univariate probit estimation; IV estimation using recursive bivariate probit model	Without controlling for gender, both the univariate and bivariate probit results show a negative and significant relationship between obesity and probability of obtaining employment. However, after controlling for	The univariate probit results without controlling for gender are biased and invalid, reflecting that obesity is endogenous to employment. When controlling for gender, the authors fail to reject the null hypothesis of

gender, the obesity results in the probit estimations are insignificant at the 10% level.

exogeneity for females but reject at the 10% level for men.

The bivariate probit models reflect a negative and significant relationship between probability of employment and obesity for males, but an insignificant, negative relationship is reflected for females.

The instrumental variables used in the bivariate probit model are non-weak and have significant explanatory power.

---

<sup>i</sup> OLS: Ordinary Least Squares; <sup>ii</sup> ATT: Average Treatment Effect on the Treated

## IB. Descriptive statistics

**Table B.1: Variable means and proportions (waves 1 and 2)**

	Males (n=1 299)				Females (n= 1 551)				
	Wave 1		Wave 2		Wave 1		Wave 2		
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
<b>Broad Employment Status</b>									
	Unemployed	0.184	(0.014)	0.19	(0.015)	0.348	(0.018)	0.28	(0.017)
	Employed	0.816	(0.014)	0.81	(0.015)	0.652	(0.018)	0.72	(0.017)
<b>Weight Status</b>									
	Obese	0.114	(0.013)	0.145	(0.015)	0.41	(0.019)	0.461	(0.019)
	Non-Obese	0.886	(0.013)	0.855	(0.015)	0.59	(0.019)	0.539	(0.019)
<b>Age</b>									
	Age	35.174	(0.423)	37.576	(0.419)	35.597	(0.39)	37.946	(0.388)
	Age Squared	1353.001	(31.591)	1525.982	(33.173)	1374.09	(29.315)	1546.531	(30.878)
	BMI	24.133	(0.207)	24.652	(0.211)	29.256	(0.255)	29.955	(0.284)
	Education (years)	9.822	(0.137)	9.909	(0.138)	10.248	(0.115)	10.394	(0.123)
	Household size	3.679	(0.106)	3.792	(0.111)	4.916	(0.104)	5.175	(0.11)
	Log household income	8.115	(0.051)	8.338	(0.048)	8.131	(0.051)	8.375	(0.049)
<b>Race</b>									
	African	0.831	(0.017)	0.831	(0.017)	0.801	(0.018)	0.801	(0.018)
	Coloured	0.076	(0.01)	0.076	(0.01)	0.092	(0.011)	0.092	(0.011)
	Asian/Indian	0.032	(0.009)	0.032	(0.009)	0.034	(0.01)	0.034	(0.01)
	White	0.06	(0.012)	0.06	(0.012)	0.072	(0.013)	0.072	(0.013)
<b>Settlement</b>									
	Rural	0.338	(0.018)	0.325	(0.017)	0.321	(0.016)	0.315	(0.016)
	Urban	0.662	(0.018)	0.675	(0.017)	0.679	(0.016)	0.685	(0.016)
<b>Relationship status</b>									
	Not in a committed relationship	0.511	(0.02)	0.498	(0.02)	0.536	(0.019)	0.546	(0.019)
	In a committed relationship	0.489	(0.02)	0.502	(0.02)	0.464	(0.019)	0.454	(0.019)
<b>Province</b>									
	Western Cape	0.058	(0.009)	0.058	(0.009)	0.082	(0.011)	0.083	(0.011)
	Eastern Cape	0.08	(0.009)	0.078	(0.009)	0.104	(0.01)	0.102	(0.01)
	Northern Cape	0.027	(0.003)	0.027	(0.003)	0.02	(0.002)	0.021	(0.002)
	Free State	0.06	(0.007)	0.059	(0.007)	0.069	(0.007)	0.065	(0.007)
	KwaZulu-Natal	0.176	(0.014)	0.175	(0.014)	0.207	(0.015)	0.209	(0.015)
	North West	0.094	(0.011)	0.09	(0.011)	0.065	(0.008)	0.065	(0.008)
	Gauteng	0.353	(0.022)	0.362	(0.022)	0.304	(0.02)	0.309	(0.02)
	Mpumalanga	0.074	(0.009)	0.075	(0.009)	0.082	(0.008)	0.083	(0.008)
	Limpopo	0.078	(0.01)	0.077	(0.01)	0.067	(0.009)	0.063	(0.008)
<b>Home Language</b>									
	IsiNdebele	0.014	(0.005)	0.015	(0.006)	0.024	(0.006)	0.023	(0.006)
	IsiXhosa	0.109	(0.011)	0.11	(0.011)	0.149	(0.013)	0.152	(0.013)
	IsiZulu	0.257	(0.018)	0.242	(0.017)	0.238	(0.015)	0.231	(0.015)
	Sepedi	0.124	(0.015)	0.13	(0.015)	0.102	(0.012)	0.108	(0.012)
	Sesotho	0.11	(0.012)	0.1	(0.011)	0.117	(0.01)	0.122	(0.01)
	Setswana	0.134	(0.013)	0.139	(0.014)	0.106	(0.012)	0.098	(0.01)
	SiSwati	0.032	(0.005)	0.033	(0.006)	0.026	(0.004)	0.026	(0.004)
	Tshivenda	0.015	(0.006)	0.011	(0.005)	0.008	(0.003)	0.008	(0.003)
	IsiTsonga	0.027	(0.007)	0.037	(0.008)	0.025	(0.006)	0.029	(0.007)
	Afrikaans	0.112	(0.014)	0.112	(0.014)	0.119	(0.014)	0.123	(0.014)
	English	0.066	(0.012)	0.07	(0.012)	0.086	(0.014)	0.081	(0.014)
<b>Emotional Wellbeing</b>									
	Poor / Fair	0.099	(0.011)	0.048	(0.008)	0.162	(0.014)	0.089	(0.011)
	Good / Very Good	0.509	(0.02)	0.449	(0.02)	0.51	(0.019)	0.504	(0.019)
	Excellent	0.392	(0.02)	0.503	(0.02)	0.328	(0.018)	0.407	(0.019)
<b>Physical Health</b>									
	Poor physical health	0.662	(0.02)	0.714	(0.019)	0.848	(0.014)	0.868	(0.013)
	Good physical health	0.338	(0.02)	0.286	(0.019)	0.152	(0.014)	0.132	(0.013)
<b>Mental Health</b>									
	Always Depressed	0.004	(0.002)	0.002	(0.001)	0.016	(0.005)	0.004	(0.001)
	Often Depressed	0.211	(0.016)	0.144	(0.014)	0.282	(0.017)	0.17	(0.014)
	Occasionally Depressed	0.758	(0.017)	0.8	(0.016)	0.674	(0.018)	0.796	(0.015)
	Never Depressed	0.027	(0.007)	0.054	(0.01)	0.028	(0.007)	0.03	(0.007)

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

## IC. Regression results

**Table C.1:** *Bivariate probit estimation results for wave 1 and wave 2*

	Wave 1				Wave 2			
	Coef.	Std. Err.	z	Sig.	Coef.	Std. Err.	z	Sig.
<b>Obese</b>								
Age	0.097	0.026	3.660	***	0.070	0.029	2.370	**
Age squared	0.001	0.000	-2.770	***	0.001	0.000	-1.380	
Gender	1.073	0.085	12.630	***	0.964	0.087	11.020	***
<b>Race</b>								
Coloured	0.319	0.333	-0.960		0.046	0.385	-0.120	
Asian/Indian	0.689	0.470	-1.460		1.256	0.548	-2.290	**
White	0.258	0.359	-0.720		0.048	0.408	-0.120	
Settlement	0.001	0.097	-0.010		0.107	0.105	1.020	
Relationship status	0.177	0.086	2.060	**	0.300	0.094	3.200	***
<b>Province</b>								
Eastern Cape	-0.018	0.229	-0.080		0.233	0.255	0.910	
Northern Cape	0.038	0.201	0.190		0.059	0.208	0.280	
Free State	0.077	0.264	0.290		0.376	0.280	1.340	
KwaZulu-Natal	0.166	0.280	0.590		0.660	0.318	2.070	**
North West	0.045	0.291	0.160		0.226	0.282	0.800	
Gauteng	0.077	0.238	0.320		0.237	0.244	0.970	
Mpumalanga	0.114	0.272	0.420		0.407	0.276	1.470	
Limpopo	0.360	0.313	-1.150		0.304	0.323	0.940	
Education	0.014	0.013	1.080		0.054	0.013	4.160	***
Household size	0.014	0.015	-0.900		0.003	0.015	0.220	
Log household income	0.152	0.050	3.070	***	0.098	0.048	2.020	**
<b>Home language</b>								
IsiXhosa	0.433	0.310	1.400		0.444	0.304	1.460	
IsiZulu	0.349	0.270	1.290		0.260	0.271	0.960	
Sepedi	0.447	0.297	1.510		0.189	0.287	0.660	
Sesotho	0.379	0.273	1.390		0.208	0.277	0.750	
Setswana	0.118	0.292	0.400		0.281	0.285	0.990	
SiSwati	0.215	0.307	0.700		0.180	0.319	0.560	
Tshivenda	0.255	0.441	-0.580		0.259	0.433	0.600	
IsiTonga	0.039	0.362	-0.110		0.009	0.322	-0.030	
Afrikaans	0.626	0.398	1.570		0.332	0.459	0.720	
English	0.137	0.405	0.340		0.053	0.452	-0.120	
<b>Emotional wellbeing</b>								
Good / Very good	0.201	0.110	-1.820	*	0.028	0.151	0.180	
Excellent	0.357	0.125	-2.850	***	0.017	0.160	0.110	
Physical health	0.307	0.111	-2.760	***	0.190	0.119	-1.600	
<b>Mental health</b>								
Often Depressed	0.178	0.313	0.570		0.837	0.725	1.160	
Occasionally depressed	0.217	0.310	0.700		0.578	0.719	0.800	
Not depressed	0.133	0.385	0.340		0.613	0.766	0.800	
<b>Broad Employment</b>								
Age	0.038	0.027	1.410		0.108	0.028	3.840	***
Age squared	0.000	0.000	0.150		0.001	0.000	-3.170	***
Gender	0.551	0.079	-7.010	***	0.259	0.088	-2.920	***
<b>Race</b>								

Coloured	0.496	0.284	-1.750	*	0.355	0.290	-1.230	
Asian/Indian	-1.328	0.501	-2.650	***	1.159	0.514	-2.260	**
White	0.261	0.434	-0.600		-0.026	0.449	-0.060	
Settlement	0.039	0.089	0.440		0.185	0.098	1.890	*
Relationship status	0.067	0.087	-0.770		-0.185	0.093	-2.000	**
Province								
Eastern Cape	0.484	0.224	-2.170	**	0.051	0.258	-0.200	
Northern Cape	0.688	0.210	-3.270	***	0.037	0.255	-0.150	
Free State	1.229	0.273	-4.500	***	-0.008	0.329	-0.020	
KwaZulu-Natal	0.507	0.278	-1.820	*	0.047	0.327	-0.140	
North West	0.967	0.264	-3.660	***	0.043	0.335	-0.130	
Gauteng	0.915	0.243	-3.760	***	0.019	0.294	-0.060	
Mpumalanga	0.967	0.278	-3.480	***	0.142	0.314	0.450	
Limpopo	0.936	0.306	-3.060	***	0.112	0.348	0.320	
Education	0.015	0.013	-1.110		0.018	0.014	-1.270	
Household size	0.108	0.016	-6.840	***	0.117	0.013	-8.730	***
Log household income	0.716	0.060	11.970	***	0.594	0.055	10.760	***
Home language								
IsiXhosa	0.491	0.356	-1.380		0.336	0.327	1.030	
IsiZulu	-0.167	0.327	-0.510		0.045	0.290	0.150	
Sepedi	0.102	0.356	-0.290		0.069	0.301	0.230	
Sesotho	0.041	0.335	-0.120		0.091	0.295	-0.310	
Setswana	0.083	0.343	-0.240		0.011	0.309	-0.040	
SiSwati	0.383	0.363	1.060		0.121	0.302	-0.400	
Tshivenda	0.312	0.517	0.600		0.087	0.504	0.170	
IsiTonga	0.192	0.398	0.480		0.222	0.317	0.700	
Afrikaans	0.288	0.413	-0.700		0.302	0.404	0.750	
English	0.103	0.463	0.220		0.952	0.475	2.000	**
Emotional wellbeing								
Good / Very good	0.002	0.130	0.010		0.230	0.173	1.330	
Excellent	0.084	0.138	-0.610		0.167	0.173	0.970	
Physical health	0.088	0.099	0.900		0.134	0.109	-1.230	
Mental health								
Often Depressed	0.155	0.379	-0.410		0.771	0.440	1.750	*
Occasionally depressed	-0.038	0.379	-0.100		0.669	0.432	1.550	
Not depressed	0.663	0.478	-1.380		0.750	0.502	1.490	
<hr/>								
Observations	2850				2850			
Pseudo $R^2$	0.0297				0.0304			
$\rho$	0.0297				0.0304			
Wald test $\rho = 0$	$\chi^2(1) = 0.2624$				$\chi^2(1) = 0.2878$			
(p-value)	(0.6085)				(0.5916)			

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table C.2: Marginal effects for bivariate probit estimations**

	Wave 1				Wave 2			
	dy/dx	Std. Err.	z	Sig.	dy/dx	Std. Err.	z	Sig.
<b>Broad Employment / Obese</b>								
Age	0.021	0.005	3.910	***	0.022	0.006	3.420	***
Age squared	0.000	0.000	-2.600	***	0.000	0.000	-2.280	**
Gender	0.174	0.015	12.010	***	0.190	0.017	11.450	***
<b>Race</b>								
Coloured	-0.083	0.054	-1.540		-0.033	0.083	-0.400	
Asian/Indian	-0.158	0.043	-3.640	***	-0.209	0.041	-5.160	***
White	-0.061	0.061	-1.010		-0.012	0.097	-0.120	
Settlement	0.002	0.020	0.110		0.034	0.023	1.480	
Relationship status	0.030	0.018	1.720	*	0.053	0.020	2.600	***
<b>Province</b>								
Eastern Cape	-0.024	0.051	-0.460		0.043	0.051	0.830	
Northern Cape	-0.023	0.045	-0.520		0.009	0.039	0.240	
Free State	-0.050	0.057	-0.890		0.075	0.056	1.350	
KwaZulu-Natal	0.014	0.064	0.220		0.137	0.066	2.080	**
North West	-0.038	0.063	-0.610		0.041	0.054	0.770	
Gauteng	-0.029	0.053	-0.550		0.045	0.045	1.000	
Mpumalanga	-0.026	0.059	-0.440		0.092	0.055	1.660	*
Limpopo	-0.103	0.060	-1.700	*	0.067	0.063	1.050	
Education	0.002	0.003	0.700		0.011	0.003	3.600	***
Household size	-0.009	0.003	-2.860	***	-0.007	0.003	-2.030	**
Log household income	0.072	0.010	7.110	***	0.058	0.010	5.540	***
<b>Home language</b>								
IsiXhosa	0.049	0.054	0.910		0.116	0.061	1.890	*
IsiZulu	0.055	0.048	1.160		0.054	0.051	1.070	
Sepedi	0.079	0.054	1.470		0.041	0.053	0.770	
Sesotho	0.069	0.049	1.400		0.034	0.052	0.660	
Setswana	0.017	0.051	0.330		0.055	0.055	0.990	
SiSwati	0.055	0.058	0.950		0.027	0.062	0.430	
Tshivenda	-0.031	0.069	-0.450		0.057	0.093	0.610	
IsiTonga	0.000	0.064	0.000		0.009	0.060	0.150	
Afrikaans	0.102	0.078	1.310		0.087	0.104	0.830	
English	0.028	0.075	0.380		0.024	0.095	0.250	
<b>Emotional wellbeing</b>								
Good / Very good	-0.041	0.023	-1.800	*	0.021	0.033	0.630	
Excellent	-0.076	0.025	-3.040	***	0.014	0.034	0.430	
Physical health	-0.054	0.022	-2.460	**	-0.049	0.026	-1.890	*
<b>Mental health</b>								
Often Depressed	0.024	0.048	0.510		0.192	0.095	2.020	**
Occasionally depressed	0.039	0.047	0.820		0.128	0.092	1.390	
Not depressed	-0.016	0.065	-0.240		0.140	0.109	1.280	

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table C.3: Recursive bivariate probit estimation results for wave 1 and wave 2**

	Wave 1				Wave 2			
	Coef.	Std. Err.	z	Sig.	Coef.	Std. Err.	z	Sig.
<b>Obese</b>								
Age	0.097	0.028	3.520	***	0.070	0.030	2.370	**
Age squared	-0.001	0.000	-2.700	***	0.001	0.000	-1.380	
Gender	1.073	0.085	12.600	***	0.964	0.087	11.020	***
<b>Race</b>								
Coloured	-0.319	0.333	-0.960		0.040	0.391	-0.100	
Asian/Indian	-0.688	0.472	-1.460		1.247	0.559	-2.230	**
White	-0.258	0.360	-0.720		0.042	0.415	-0.100	
Settlement	-0.001	0.097	-0.010		0.106	0.105	1.010	
Relationship status	0.177	0.092	1.920	*	0.298	0.096	3.110	***
<b>Province</b>								
Eastern Cape	-0.018	0.230	-0.080		0.234	0.255	0.920	
Northern Cape	0.038	0.202	0.190		0.059	0.208	0.280	
Free State	0.077	0.265	0.290		0.375	0.281	1.340	
KwaZulu-Natal	0.166	0.284	0.580		0.660	0.318	2.070	**
North West	0.045	0.292	0.150		0.224	0.283	0.790	
Gauteng	0.076	0.241	0.320		0.238	0.245	0.970	
Mpumalanga	0.114	0.273	0.420		0.409	0.278	1.470	
Limpopo	-0.361	0.314	-1.150		0.305	0.324	0.940	
Education	0.014	0.013	1.080		0.055	0.013	4.100	***
Household size	-0.014	0.015	-0.890		0.003	0.015	0.230	
Log household income	0.152	0.050	3.030	***	0.097	0.048	2.020	**
<b>Home language</b>								
IsiXhosa	0.433	0.311	1.400		0.447	0.305	1.460	
IsiZulu	0.349	0.275	1.270		0.264	0.272	0.970	
Sepedi	0.448	0.297	1.510		0.189	0.287	0.660	
Sesotho	0.380	0.275	1.380		0.211	0.280	0.760	
Setswana	0.119	0.293	0.400		0.288	0.294	0.980	
SiSwati	0.214	0.308	0.700		0.180	0.319	0.560	
Tshivenda	-0.254	0.443	-0.570		0.259	0.435	0.600	
IsiTonga	-0.038	0.364	-0.110		0.014	0.327	-0.040	
Afrikaans	0.626	0.398	1.570		0.327	0.464	0.710	
English	0.138	0.408	0.340		0.055	0.454	-0.120	
<b>Emotional wellbeing</b>								
Good / Very good	-0.201	0.111	-1.810	*	0.026	0.152	0.170	
Excellent	-0.356	0.127	-2.800	***	0.017	0.159	0.110	
Physical health	-0.307	0.112	-2.740	***	0.190	0.119	-1.590	

Mental health							
Often Depressed	0.179	0.314	0.570		0.824	0.723	1.140
Occasionally depressed	0.218	0.311	0.700		0.563	0.720	0.780
Not depressed	0.133	0.385	0.350		0.594	0.780	0.760
<hr/>							
Broad Employment							
Obese	0.014	0.492	0.030		0.098	0.712	0.140
Age	0.038	0.028	1.360		0.106	0.031	3.410 ***
Age squared	0.000	0.000	0.150		0.001	0.000	-3.040 ***
Gender	-0.555	0.156	-3.550	***	0.285	0.209	-1.360
Race							
Coloured	-0.495	0.287	-1.720	*	0.352	0.288	-1.220
Asian/Indian	-1.326	0.507	-2.620	***	1.128	0.572	-1.970 **
White	-0.261	0.435	-0.600		0.025	0.446	-0.060
Settlement	0.039	0.089	0.440		0.183	0.101	1.810 *
Relationship status	-0.067	0.088	-0.770		0.193	0.106	-1.830 *
Province							
Eastern Cape	-0.484	0.224	-2.170	**	0.059	0.260	-0.230
Northern Cape	-0.688	0.210	-3.270	***	0.039	0.254	-0.150
Free State	-1.229	0.273	-4.500	***	0.020	0.337	-0.060
KwaZulu-Natal	-0.508	0.281	-1.810	*	0.065	0.355	-0.180
North West	-0.967	0.264	-3.660	***	0.050	0.336	-0.150
Gauteng	-0.916	0.243	-3.770	***	0.027	0.295	-0.090
Mpumalanga	-0.968	0.280	-3.460	***	0.129	0.325	0.400
Limpopo	-0.935	0.306	-3.060	***	0.102	0.355	0.290
Education	-0.015	0.013	-1.090		0.019	0.017	-1.110
Household size	-0.108	0.016	-6.860	***	0.117	0.013	-8.700 ***
Log household income	0.715	0.061	11.650	***	0.590	0.063	9.320 ***
Home language							
IsiXhosa	-0.493	0.361	-1.370		0.323	0.340	0.950
IsiZulu	-0.169	0.329	-0.510		0.038	0.292	0.130
Sepedi	-0.104	0.357	-0.290		0.064	0.303	0.210
Sesotho	-0.043	0.340	-0.130		0.096	0.298	-0.320
Setswana	-0.083	0.344	-0.240		0.018	0.314	-0.060
SiSwati	0.383	0.362	1.060		0.124	0.302	-0.410
Tshivenda	0.311	0.515	0.600		0.079	0.505	0.160
IsiTonga	0.192	0.398	0.480		0.222	0.317	0.700
Afrikaans	-0.291	0.422	-0.690		0.291	0.411	0.710
English	0.102	0.463	0.220		0.947	0.472	2.010 **
Emotional wellbeing							

Good / Very good	0.003	0.126	0.020	0.229	0.173	1.330
Excellent	-0.082	0.140	-0.590	0.167	0.173	0.960
Physical health	0.089	0.101	0.880	0.130	0.115	-1.130
Mental health						
Often Depressed	-0.156	0.383	-0.410	0.737	0.501	1.470
Occasionally depressed	-0.040	0.383	-0.100	0.643	0.465	1.380
Not depressed	-0.664	0.482	-1.380	0.723	0.543	1.330

---

Observations	2850	2850
Pseudo $R^2$	0.0215	0.0882
$\rho$	0.0215	0.0880
Wald test $\rho = 0$	$\chi^2(1) = 0.0566$	$\chi^2(1) = 0.0456$
(p-value)	(0.9400)	(0.8310)

---

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table C.4: Marginal effects for recursive bivariate probit estimations**

	Wave 1				Wave 2			
	dy/dx	Std. Err.	z	Sig.	dy/dx	Std. Err.	z	Sig.
<b>Broad employment</b>								
Obese	0.001	0.029	0.030		0.006	0.047	0.130	
Age	0.021	0.005	3.930	***	0.022	0.006	3.480	***
Age squared	0.000	0.000	-2.620	***	0.000	0.000	-2.320	**
Gender	0.174	0.026	6.670	***	0.186	0.034	5.510	***
<b>Race</b>								
Coloured	-0.083	0.054	-1.540		-0.032	0.083	-0.390	
Asian/Indian	-0.158	0.045	-3.550	***	-0.206	0.048	-4.280	***
White	-0.061	0.061	-1.010		-0.011	0.097	-0.110	
Settlement	0.002	0.020	0.110		0.034	0.023	1.490	
Relationship status	0.030	0.020	1.500		0.051	0.025	2.050	**
<b>Province</b>								
Eastern Cape	-0.024	0.052	-0.460		0.042	0.051	0.830	
Northern Cape	-0.023	0.046	-0.510		0.009	0.039	0.230	
Free State	-0.051	0.059	-0.870		0.074	0.057	1.300	
KwaZulu-Natal	0.013	0.066	0.200		0.135	0.066	2.030	**
North West	-0.039	0.064	-0.610		0.040	0.054	0.740	
Gauteng	-0.030	0.056	-0.530		0.045	0.045	0.990	
Mpumalanga	-0.026	0.061	-0.430		0.091	0.054	1.680	*
Limpopo	-0.103	0.061	-1.690	*	0.066	0.063	1.060	
Education	0.002	0.003	0.700		0.010	0.003	3.430	***
Household size	-0.009	0.003	-2.870	***	-0.007	0.003	-1.980	**
Log household income	0.072	0.010	7.100	***	0.059	0.011	5.180	***
<b>Home language</b>								
IsiXhosa	0.049	0.054	0.900		0.115	0.060	1.910	*
IsiZulu	0.055	0.047	1.160		0.054	0.050	1.080	
Sepedi	0.079	0.054	1.470		0.040	0.052	0.780	
Sesotho	0.069	0.049	1.400		0.034	0.051	0.670	
Setswana	0.017	0.051	0.330		0.055	0.055	1.010	
SiSwati	0.055	0.058	0.940		0.026	0.061	0.430	
Tshivenda	-0.031	0.070	-0.450		0.056	0.093	0.600	
IsiTonga	0.000	0.064	0.000		0.009	0.060	0.140	
Afrikaans	0.102	0.078	1.300		0.085	0.105	0.810	
English	0.029	0.075	0.380		0.025	0.094	0.270	
<b>Emotional wellbeing</b>								
Good / Very good	-0.041	0.023	-1.760	*	0.021	0.032	0.640	
Excellent	-0.075	0.027	-2.800	***	0.015	0.034	0.440	
Physical health	-0.054	0.022	-2.470	**	-0.049	0.026	-1.860	*
<b>Mental health</b>								
Often Depressed	0.024	0.048	0.510		0.189	0.097	1.940	*
Occasionally depressed	0.039	0.047	0.820		0.124	0.094	1.330	
Not depressed	-0.016	0.065	-0.240		0.136	0.115	1.180	

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table C.5: Recursive bivariate probit estimation results where broad employment is a regressor for obesity**

	Wave 1				Wave 2			
	Coef.	Std. Err.	z	Sig.	Coef.	Std. Err.	z	Sig.
<b>Broad Employment</b>								
Age	0.037	0.027	1.39		0.109	0.028	3.92	***
Age squared	0.000	0.000	0.17		0.001	0.000	-3.23	***
Gender	0.552	0.078	-7.03	***	0.278	0.089	-3.14	***
<b>Race</b>								
Coloured	0.522	0.285	-1.83	**	0.433	0.291	-1.49	
Asian/Indian	1.360	0.504	-2.7	***	1.246	0.528	-2.36	**
White	0.346	0.451	-0.77		0.251	0.478	-0.52	
Settlement	0.039	0.089	0.43		0.171	0.102	1.68	*
Relationship status	0.063	0.087	-0.72		-0.197	0.094	-2.1	**
<b>Province</b>								
Eastern Cape	-0.475	0.225	-2.11	**	0.009	0.266	-0.03	
Northern Cape	-0.683	0.209	-3.27	***	-0.050	0.249	-0.2	
Free State	1.212	0.276	-4.39	***	0.033	0.326	0.1	
KwaZulu-Natal	0.505	0.278	-1.82	*	0.015	0.325	-0.05	
North West	0.958	0.266	-3.61	***	0.044	0.331	-0.13	
Gauteng	0.908	0.244	-3.73	***	0.024	0.292	0.08	
Mpumalanga	-0.955	0.279	-3.43	***	0.168	0.310	0.54	
Limpopo	0.925	0.309	-3	***	0.166	0.351	0.47	
Education	-0.015	0.013	-1.15		0.018	0.014	-1.3	
Household size	0.109	0.016	-6.93	***	0.117	0.014	-8.63	***
Log household income	0.715	0.060	12.01	***	0.593	0.055	10.76	***
<b>Home language</b>								
IsiXhosa	0.488	0.358	-1.36		0.327	0.321	1.02	
IsiZulu	0.158	0.330	-0.48		0.065	0.286	0.23	
Sepedi	0.094	0.360	-0.26		0.077	0.297	0.26	
Sesotho	0.052	0.337	-0.15		0.062	0.292	-0.21	
Setswana	0.075	0.345	-0.22		0.043	0.314	0.14	
SiSwati	0.397	0.367	1.08		0.088	0.302	-0.29	
Tshivenda	0.301	0.519	0.58		0.114	0.490	0.23	
IsiTonga	0.186	0.398	0.47		0.257	0.314	0.82	
Afrikaans	0.252	0.415	-0.61		0.447	0.419	1.07	
English	0.150	0.472	0.32		1.019	0.493	2.07	**
<b>Emotional wellbeing</b>								
Good / Very good	0.005	0.131	0.04		0.185	0.183	1.01	
Excellent	0.082	0.139	-0.59		0.114	0.184	0.62	
Physical health	0.082	0.099	0.82		0.131	0.108	-1.21	
<b>Mental health</b>								
Often Depressed	0.129	0.381	-0.34		0.816	0.461	1.77	*
Occasionally depressed	-0.010	0.381	-0.03		0.693	0.455	1.52	
Not depressed	0.636	0.476	-1.34		0.825	0.517	1.6	
<b>Obese</b>								
Broad Employment	0.320	0.426	-0.75		0.845	0.679	-1.24	
Age	0.104	0.027	3.83	***	0.088	0.030	2.91	***
Age squared	0.001	0.000	-2.94	***	0.001	0.000	-1.91	*
Gender	1.029	0.111	9.29	***	0.884	0.139	6.38	***
<b>Race</b>								
Coloured	0.337	0.334	-1.01		0.090	0.387	-0.23	

Asian/Indian	0.757	0.476	-1.59		1.316	0.555	-2.37	**
White	0.300	0.356	-0.84		0.130	0.411	-0.32	
Settlement	0.004	0.096	-0.04		0.142	0.108	1.32	
Relationship status	0.170	0.087	1.95	*	0.258	0.109	2.37	**
Province								
Eastern Cape	0.043	0.230	-0.19		0.205	0.251	0.82	
Northern Cape	0.009	0.212	-0.04		0.034	0.204	0.16	
Free State	0.002	0.286	-0.01		0.340	0.276	1.23	
KwaZulu-Natal	0.130	0.280	0.47		0.587	0.302	1.94	*
North West	0.016	0.308	-0.05		0.194	0.276	0.7	
Gauteng	0.021	0.249	0.09		0.212	0.238	0.89	
Mpumalanga	0.053	0.283	0.19		0.404	0.267	1.51	
Limpopo	0.420	0.318	-1.32		0.311	0.304	1.02	
Education	0.012	0.014	0.86		0.046	0.014	3.23	***
Household size	0.022	0.019	-1.16		0.022	0.026	-0.84	
Log household income	0.204	0.086	2.39	**	0.212	0.105	2.02	**
Home language								
IsiXhosa	0.396	0.311	1.27		0.470	0.286	1.64	
IsiZulu	0.340	0.267	1.28		0.253	0.258	0.98	
Sepedi	0.436	0.292	1.49		0.190	0.265	0.72	
Sesotho	0.376	0.270	1.39		0.176	0.266	0.66	
Setswana	0.114	0.289	0.4		0.264	0.274	0.96	
SiSwati	0.232	0.304	0.76		0.123	0.313	0.39	
Tshivenda	0.241	0.441	-0.55		0.276	0.420	0.66	
IsiTonga	0.025	0.363	-0.07		0.018	0.306	0.06	
Afrikaans	0.600	0.394	1.52		0.353	0.455	0.78	
English	0.126	0.401	0.31		0.002	0.443	0	
Emotional wellbeing								
Good / Very good	-0.197	0.107	-1.84	*	0.068	0.150	0.46	
Excellent	0.356	0.122	-2.92	***	0.044	0.157	0.28	
Physical health	0.301	0.112	-2.69	***	0.220	0.115	-1.91	*
Mental health								
Often Depressed	0.156	0.295	0.53		1.040	0.759	1.37	
Occasionally depressed	0.202	0.290	0.69		0.755	0.753	1	
Not depressed	0.070	0.384	0.18		0.774	0.794	0.97	
<hr/>								
Observations	2850				2850			
Pseudo $R^2$	0.2133				0.4956			
$\rho$	0.2101				0.4586			
Wald test $\rho = 0$	$\chi^2(1) = 0.6834$				$\chi^2(1) = 1.0619$			
(p-value)	(0.4084)				(0.3028)			

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table C.6: Univariate probit estimation results**

Transitioned to Obese	Coef.	Std. Err.	z	Sig.
<b>Labour Market State Transition</b>				
Transition from NEA to Unemployed	0.014	0.093	0.150	
Transition from NEA to Employed	0.159	0.085	1.860	*
Transition from Unemployed to NEA	-0.020	0.073	-0.280	
Transition from Unemployed to Employed	0.029	0.091	0.320	
Transition from Employed to NEA	-0.060	0.065	-0.940	
Transition from Employed to Unemployed	-0.085	0.106	-0.810	
Gender	0.252	0.046	5.440	***
Age	0.032	0.010	3.250	***
Age squared	-0.000	0.000	-2.930	***
<b>Race</b>				
Coloured	0.151	0.247	0.610	
Asian/Indian	-1.739	0.325	-5.350	***
White	0.024	0.272	0.090	
Settlement	-0.024	0.054	-0.450	
Education	0.020	0.007	2.980	***
Log household income	0.029	0.026	1.140	
Relationship status	0.186	0.049	3.770	***
<b>Province</b>				
Eastern Cape	0.527	0.137	3.860	***
Northern Cape	-0.103	0.149	-0.690	
Free State	0.197	0.170	1.160	
KwaZulu-Natal	0.507	0.151	3.360	***
North West	0.006	0.182	0.030	
Gauteng	0.123	0.150	0.820	
Mpumalanga	0.397	0.161	2.460	**
Limpopo	0.408	0.177	2.310	**
Household size	0.005	0.007	0.680	
<b>Home language</b>				
IsiXhosa	-0.110	0.103	-1.070	
IsiZulu	0.116	0.222	0.520	
Sepedi	-0.152	0.111	-1.370	
Sesotho	-0.045	0.115	-0.390	
Setswana	0.173	0.118	1.470	
SiSwati	-0.254	0.132	-1.920	*
Tshivenda	0.102	0.176	0.580	
IsiTonga	-0.281	0.140	-2.000	**
Afrikaans	-0.108	0.257	-0.420	
English	-0.034	0.260	-0.130	
<b>Emotional wellbeing</b>				
Good / Very good	0.197	0.066	2.980	**
Excellent	0.230	0.072	3.190	***
Physical health	0.012	0.064	0.190	
<b>Mental health</b>				
Often Depressed	-0.034	0.171	-0.200	
Ocassionally depressed	-0.094	0.169	-0.560	
Not depressed	-0.205	0.222	-0.920	
Constant	-2.900	0.320	-9.060	*
Observations	14427			
Pseudo $R^2$	0.0461			
Wald test $\rho = 0$	$\chi^2(41) = 261.150$			
(p-value)	(0.0000)			

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)

**Table C.7: Marginal effects for univariate probit estimation**

Transitioned to Obese	dy/dx	Std. Err.	z	Sig.
<b>Labour Market State Transition</b>				
Transition from NEA to Unemployed	0.002	0.016	0.150	
Transition from NEA to Employed	0.029	0.017	1.720	*
Transition from Unemployed to NEA	-0.003	0.012	-0.280	
Transition from Unemployed to Employed	0.005	0.016	0.310	
Transition from Employed to NEA	-0.010	0.010	-0.960	
Transition from Employed to Unemployed	-0.013	0.016	-0.840	
Gender	0.042	0.008	5.550	***
Age	0.005	0.002	3.220	***
Age squared	-0.000	0.000	-2.910	***
<b>Race</b>				
Coloured	0.028	0.049	0.570	
Asian/Indian	-0.099	0.008	-12.950	***
White	0.004	0.047	0.090	
Settlement	-0.004	0.009	-0.450	
Education	0.003	0.001	2.970	***
Log household income	0.005	0.004	1.140	
Relationship status	0.031	0.008	3.770	***
<b>Province</b>				
Eastern Cape	0.085	0.020	4.150	***
Northern Cape	-0.011	0.015	-0.690	
Free State	0.025	0.021	1.180	
KwaZulu-Natal	0.081	0.021	3.880	***
North West	0.001	0.020	0.030	
Gauteng	0.015	0.017	0.860	
Mpumalanga	0.059	0.022	2.650	***
Limpopo	0.061	0.026	2.360	**
Household size	0.001	0.001	0.680	
<b>Home language</b>				
IsiXhosa	-0.018	0.017	-1.080	
IsiZulu	0.022	0.044	0.490	
Sepedi	-0.024	0.017	-1.400	
Sesotho	-0.008	0.019	-0.400	
Setswana	0.034	0.024	1.420	
SiSwati	-0.038	0.018	-2.110	**
Tshivenda	0.019	0.034	0.560	
IsiTonga	-0.042	0.019	-2.210	**
Afrikaans	-0.018	0.041	-0.440	
English	-0.006	0.044	-0.130	
<b>Emotional wellbeing</b>				
Good / Very good	0.029	0.009	3.240	***
Excellent	0.035	0.010	3.400	***
Physical health	0.002	0.011	0.190	
<b>Mental health</b>				
Often Depressed	-0.006	0.031	-0.200	
Occasionally depressed	-0.016	0.031	-0.530	
Not depressed	-0.033	0.037	-0.900	

Source: own calculations using NIDS wave 1 (2008) and wave 2 (2010:2011)