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Only the Fit Survive Recessions: Estimating Labor Market Penalties for the Obese Over the Business Cycle

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Only the Fit Survive Recessions: Estimating Labor Market Penalties for the Obese Over the Business Cycle *

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Abstract

There is evidence of labor market discrimination against minority groups based on race, gender, beauty and other characteristics. Using two national surveys, I measure labor market differentials between obese and healthy weight workers over business cycle fluctuations. I find that during economic downturns, obese individuals experience larger declines in income relative to those who are not obese. These findings are robust to the inclusion of occupation fixed effects, suggesting the findings cannot be fully explained by obese workers selecting careers that tend to have greater sensitivity to business cycle fluctuations.

Keywords: obesity, business cycle, discrimination

JEL Classification: J71, I14, E29

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*Rachel Inafuku is an economist at the University of Hawai‘i at Mānoa. I would like to thank Tim Halliday and Teresa Molina for the feedback that they have contributed to this paper. This paper uses restricted data from the National Longitudinal Survey of Youth (NLSY) ’97 cohort. The data can be obtained by filing an application with the Bureau of Labor Statistics (https://www.bls.gov/nls/geocodeapp.htm). This paper also uses data from the Behavioral Risk Factor Surveillance System (BRFSS) and can be obtained directly from the BRFSS website (https://www.cdc.gov/brfss/index.html). Please email the author for assistance.

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1 Introduction

Though there are anti-discrimination laws in place to protect vulnerable groups, labor market discrimination still exists. Most of the discrimination literature has been built on Becker's *The Economics of Discrimination*, which introduced the first model of employer taste-based discrimination in which employers' prejudice can harm labor outcomes for minority workers (Becker, 2010). Previous studies have shown that substantial discrimination exists based on gender, race, and even appearance (Bertrand and Hallock, 2001; Bertrand and Mullainathan, 2004; Hamermesh and Biddle, 1994). Furthermore, discrimination can lead to bigger wage gaps during looser labor markets as shown in Biddle and Hamermesh (2013) and Carlsson et al. (2018).

In this paper, I present new evidence on how discrimination against obese workers manifests itself over the business cycle. Analyzing the interplay between labor market outcomes, the business cycle, and obesity can shed some insights into possible labor market discrimination faced by obese workers. To better understand this, I note that during recessions, labor supply exceeds the demand for labor, which gives employers greater bargaining power and thereby increases the scope for discrimination. Given this, we could expect labor market gaps to widen during economic downturns due to discrimination.

The obesity epidemic is a growing concern in the United States. According to the Center for Disease Control (CDC), the average American adult is overweight.[1] Between 1999 and 2018, the prevalence of obesity increased by nearly nine percentage points (Fryar et al., 2018). Currently, the US adult obesity rate is over 40% (Fryar et al., 2018). Although there have been a number of initiatives aimed at combating the obesity epidemic, the US obesity rate has grown at an increasing rate. Obesity is not only associated with a number of health conditions (Calle and Thun, 2004; Hossain et al., 2007), studies have also shown that it is associated with weaker labor market outcomes (Cawley, 2004; Pagan and Davila, 1997; Deb et al., 2011; Caliendo and Lee,

[1] According to the CDC, an individual who is overweight has a BMI that is greater than or equal to 25 and less than 30.

2013; Baum and Ford, 2004). Most of the literature agrees that the negative impacts of obesity on labor outcomes are more prevalent amongst females (Averett and Korenmann, 1996; Caliendo and Lee, 2013; Bhattacharya and Bundorf, 2009; Pagan and Davila, 1997; Mason, 2012). For example, Cawley (2004) finds that an increase in body weight lowers wages specifically for white females. However, some have found obesity is negatively associated with labor outcomes for both genders (Baum and Ford, 2004; Morris, 2007; Rooth, 2009).

In this study, I follow the methodology of Biddle and Hamermesh (2013) to identify the causal effect of the business cycle on labor market outcomes for obese and non-obese individuals. Much like prior studies that use the business cycle to study discrimination, I look to see if obese workers see greater decreases in their income than their healthy weight peers during cyclical downturns. I include occupation fixed effects which control for the possibility of differential responses in career choices between obese and non-obese workers across the business cycle. Though there have been several studies that analyze the relationship between obesity and labor market outcomes (Cawley, 2004; Pagan and Davila, 1997; Deb et al., 2011; Caliendo and Lee, 2013; Baum and Ford, 2004), none have investigated how the business cycle impacts these differentials.

Discrimination against obese workers has been documented in laboratory settings by sociologists since 1979 (Larkin and Pines, 1979; Roehling, 1999; Rooth, 2009). Since 2008, those with severe obesity have been protected under the Americans with Disabilities Act (Shinall, 2016). However, the labor market gap between obese and non-obese workers persists. Although there are differing ideas about the mechanisms behind the obesity labor market penalty, one common explanation is employer discrimination. Despite the fact that a large percentage of the adult population is overweight or obese, there is still a stigma attached to obese workers. Agerström and Rooth (2011) argue that employers perceive heavier workers as less productive. Bhattacharya and Bundorf (2009) argue that obesity discrimination is driven by greater health risk and thus higher healthcare expenditures for companies with employer sponsored healthcare. Though previous studies have looked at the relationship between obesity and labor market outcomes, few have been able to establish a causal channel.

In this study, I use the 1997 cohort of National Longitudinal Survey of Youth (NLSY) and the Behavioral Risk Factor Surveillance System (BRFSS) for my analysis. The NLSY is a panel survey that began interviewing nearly 9,000 youths in 1997 and now conducts interviews bi-annually. The survey collects data on each individual's demographics, work history, education outcomes, health, and more. I focus on individuals ages 18 to 36 years old from the survey waves 2000-2011, 2013 and 2015. My analysis uses the NLSY's restricted data which provides each individual's residence at the county level. The granularity of county level data allows for greater variation across estimates. I also extend my analysis using the BRFSS, a repeated cross section study with over 400,000 adults interviewed annually. The BRFSS includes individuals over a more expansive age range (18-64 years old), with the trade-off of losing the ability to estimate my model with occupation fixed effects.

Using the NLSY, I find that obese workers receive lower income relative to their non-obese peers. This income gap widens during economic downturns, displaying a counter-cyclical pattern. My results are robust to the inclusion of occupation fixed effects, suggesting that these findings are not driven by obese workers differentially selecting into careers that may fluctuate relatively more with the economy. Moreover, I find that the counter-cyclical income effects are predominantly driven by obese women. Looking at weeks of employment, I find that obese men face greater decreases in the number of weeks worked over economic downturns relative to their non-obese peers. Results from the BRFSS show that the income gap between obese and healthy weight workers increases over cyclical downturns for both genders. Employment gaps are also counter-cyclical for both male and female obese workers. Taken together, I conclude that decreases in income and employment over economic downturns are larger for obese workers, which may reflect labor market discrimination.

2 Data

The empirical framework in this paper use two data sets for analysis, the National Longitudinal Survey of Youth (NLSY) and the Behavioral Risk Factor Surveillance System (BRFSS).

2.1 National Longitudinal Survey of Youth

The NLSY is a nationally representative longitudinal survey that follows a sample of American youths. The NLSY 97 cohort consists of nearly 9,000 individuals who were born between 1980 and 1984. This cohort has been surveyed 18 times thus far and are now interviewed biennially. I use the NLSY's geocode which reports each individuals county of residence during each interview round. This study uses data from the years 2000-2011, 2013 and 2015. I do not include data before 2000 since the majority of the youths in the cohort were still in primary school at that time. I also drop youths who are younger than 18 years old. Thus, the individuals in this study range from 18 to 36 years old. I use the log of the individual's income in wages, salary, commissions, or tips over the past year and also the number of weeks employed in a year as the dependent variables for my analysis. In order to capture discouraged workers in the data, I keep individuals who reported zero earnings for the year. Thus, I set income for these individuals as one dollar before taking the log.

2.2 Behavioral Risk Factor Surveillance System

The Behavioral Risk Factor Surveillance System (BRFSS) is an epidemiological surveillance survey sponsored by the Center for Disease Control (CDC) and other federal agencies. The data is a repeated cross-section survey established in 1984 that interviews roughly 400,000 American adults annually. To keep my results consistent with the NLSY, I use survey waves from the years 2000-2018. The BRFSS asks individuals to report their income within one of eight possible income brackets. I code income for each individual as the mean of their reported income bracket. For the top income bracket, I code income as the minimum of the income bracket (because there is no maximum). Respondents are asked to report their age within a 5 year bracket. I eliminate those who are over the 60-64 year old age bracket. Thus, individuals in the BRFSS sample are ages 18 to 64 years old. Though the BRFSS may be less comprehensive than the NLSY, the individuals in the BRFSS represent a wider age range of the adult population. In comparison, the NLSY samples a younger adult population. In addition, the BRFSS has a much larger sample size.

2.3 National Health and Nutrition Examination Survey

Self-reported weight tends to include some degree of misreporting error which may lead to biased estimates (Judge, 1985). In order to correct for this, I exploit both self-reported and physical examination data from the National Health and Nutrition Examination Survey (NHANES) for the years 2000-2017. The NHANES is a program conducted by the CDC that assesses the health and nutritional status of US adults and youths. A unique feature of this survey is that it includes both self-reported surveys and physical examinations for each individual. Thus, researchers can compare self-reported survey data to true values of health measures for each participant. Following the methodology of Lee and Sepanski (1995) and Bound et al. (2001), I regress actual weight onto self-reported weight and its square for each gender by race. I then predict actual weight using self-reported weight in both the NLSY and BRFSS. I use these body weight estimates to calculate each individual's BMI in the NLSY and the BRFSS.

2.4 Business Cycle Measure

Following numerous studies, including Biddle and Hamermesh (2013), I use the unemployment rates from the Bureau of Labor Statistics (BLS) as an indicator for the business cycle. The BLS publishes the unemployment rate monthly at the country, region, state, county and metropolitan statistical area level. The data is originally collected from the Current Employment Statistics, a monthly survey conducted by the BLS. The survey sample size includes approximately 140,000 businesses and government agencies drawn from a total of about 9 million unemployment insurance tax accounts. For the NLSY and BRFSS, I use the unemployment rate at the county-year level and state-month level, respectively.

2.5 Summary Statistics

In both data sets, I calculate each individual's body mass index[2] (BMI) using their height and weight. I then generate a dummy variable equal to one if an individual's BMI is in the obese range and zero otherwise. According to the CDC, an individual is considered obese if he or she has a BMI of 30 or greater. Since weight increases during pregnancy, and pregnant women may be subject to differential labor market conditions (Budig and England, 2001), I eliminate pregnant women. To keep my results consistent across data sets, I categorize each individual as either white, black, or 'other race.' I then eliminate self-employed workers since employer discrimination does not apply to them. However, I later run my baseline specification with a sample of self-employed workers only as a robustness check to see if there are any significant effects of the business cycle on labor market differentials for this group. I also remove active members of the armed forces, resulting in 8,694 unique individuals in the NLSY and 4,159,584 observations in the BRFSS.

Table 1 displays summary statistics for both the NLSY and BRFSS. Among those in the NLSY sample, the mean labor income is relatively low at less than $24,000 per year (in nominal US dollars). Moreover, 21% of individuals have college degrees, 22% are married and the average number of weeks employed in a year is roughly 36 weeks. These statistics represent characteristics of a much younger group. The mean age in this sample is nearly 25 years old. On the other hand, the average age in the BRFSS sample is about 45 years old. The mean income is about $48,000 (in nominal US dollars), about 93% of the sample is employed and over half

[2] Body mass index is calculated by dividing weight in kilograms by height in meters squared.

the sample is married. The individuals in the BRFSS reflect a sample much more representative of the total US working population. Furthermore, the mean unemployment rate in the NLSY sample is slightly higher than the BRFSS sample and also has a larger standard deviation. This is reflective of the greater variation in unemployment at the county level in comparison with state level unemployment rates.

Using the survey answers of body weight and the estimated true values[3], I calculate each individual's BMI. In Table 1, self-reported weight indicates the survey respondents self-reported body weight prior to correcting for measurement error. In both the NLSY and BRFSS samples, corrected values of body weight are greater than self-reported values, indicating that survey respondents tend to underreport their weight. Using the corrected values of weight, I construct a variable for BMI. The mean BMI in the NLSY sample is 27 while the mean BMI in the BRFSS sample is approximately 28. I create a dummy variable for obesity equal to 1 if an individual has a BMI of 30 or greater. In the NLSY sample, 29% of the individuals are obese while 31% of individuals in the BRFSS sample are obese.

[3]Estimated values of true body weight are found following the methodology from Lee and Sepanski (1995) and Bound et al. (2001) as described in section 2.3.

Table 1: Summary Statistics

	NLSY		BRFSS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.49	0.50	0.58	0.49
Age	24.82	4.35	45.08	12.71
Height (in.)	67.50	4.26	66.98	4.07
Self-Reported Weight (lbs.)	174.61	46.01	178.46	45.70
Estimated Weight (lbs.)	176.11	46.70	180.57	45.89
Body Mass Index	27.09	6.53	28.20	6.40
Obese	0.29	0.45	0.31	0.46
Annual Income	23,882.69	22,576.26	48,006.75	24,033.19
Weeks Employed Per Year	36.83	19.64		
Employed			0.93	0.26
Unemployment Rate	6.37	2.48	5.76	2.08
College Degree	0.21	0.41		
Attended College			0.65	0.48
White	0.57	0.50	0.81	0.39
Black	0.28	0.45	0.10	0.30
Other Race	0.15	0.36	0.09	0.29
Number of Children	0.57	0.99	0.79	1.16
Married	0.22	0.42	0.56	0.50
Urban Residence	0.81	0.40		
ASVAB Test Scores	45,243.48	29,350.72		
	N=8,694		NT=4,159,584	

†Data from the NLSY uses survey waves 2000-2013, 2015 and 2017. Data from the BRFSS uses survey waves 2000-2019. Self-reported weight indicates the individuals self-reported weight before adjusting for measurement error. Estimated weight indicates the individuals estimated weight after adjusting for measurement error. Annual income is reported in nominal US dollars. ASVAB Test Scores are age-adjusted math and verbal test scores. N represents the number of unique individuals for the NLSY. NT represents the number of person-month observations for the BRFSS.

3 Empirical Methodology and Results

3.1 NLSY Empirical Methodology

Using data from the NLSY, I analyze the effect of the business cycle on income and employment differentials between obese and healthy weight workers following the methodology of Biddle and Hamermesh (2013). My model is estimated as follows:

$$Y_{ict} = \beta_0 + \beta_1 O_{it} + \beta_2 U_{ct} + \beta_3 O_{it} * U_{ct} + \gamma X_{ict} + \delta_j + \nu_c + \tau_t + \epsilon_{ict}$$

where Y_{ict} is the log of income or the number of weeks individual i worked in county c in year t. The variable, O_{it} is a dummy variable equal to 1 if an individual is obese and 0 otherwise. The variable, U_{ct}, is the de-meaned unemployment rate reported in percentage points at the county-year level. The term X_{ict} is a vector of covariates and δ_j, ν_c, and τ_t are occupation, county and year fixed effects respectively. Standard errors are clustered at the county-year level.

Theoretically, given that the NLSY is an individual level panel, I can include individual fixed effects in my model. However, the inclusion of individual fixed effects exacerbates the attenuation bias caused by measurement error in the county level unemployment rates. The BLS collects unemployment data through a survey of roughly 140,000 businesses and government agencies and uses a time-series model to estimate true values of unemployment. However, there still exists some degree of measurement error due to the relatively small sample size of the survey, especially at the county level. Thus, including individual fixed effects with unemployment estimates that have some level of measurement error further exacerbates the attenuation bias.[4] To this end, I choose to omit individual fixed effects from my main specification. However, I later run my regression with individual fixed effects as a robustness check.

Though excluding individual fixed effects decreases the attenuation bias, it also leaves room for potential omitted variables bias due to time invariant differences across workers such as innate ability or intelligence that may influence income, occupation, or BMI. To reduce this potential endogeneity, I control for each individual's age-adjusted ASVAB math and verbal scores. The ASVAB is an aptitude test developed by the US Department of Defense that measures an individual's ability. The test is administered nationwide at over 14,000 schools annually. To

[4] On this, Deaton (1995) says, "in the standard case where measurement error induces attenuation bias, the attenuation will be worse using the difference or within estimator. The combination of loss of precision and increased attenuation bias often erases in the difference or within estimates effects that were significant in the cross-section, even when the model is correctly specified and there is no heterogeneity bias."

compute these scores, the NLSY separates each individual into 3-month age groups and implements sampling weights to adjust each individual's score according to his or her age bracket.

Additionally, it may be the case that those who are obese are more likely to select certain occupations which tend to fluctuate relatively more or less with the business cycle in comparison to careers that non-obese workers may choose. If this were the case, then in the absence of occupation fixed effects, labor market gaps would widen when the unemployment rate increases due to career choice (and not potential discrimination against the obese). Including occupation fixed effects in my estimation mitigates this potential selection bias.

I de-mean the unemployment rate to a mean of zero for both data sets. By setting the mean to zero, I can now interpret β_1 as the effect of obesity on income or employment for an individual in a given county-year with the average level of unemployment. My coefficient of interest is β_3, the interaction between the dummy variable for obesity and the unemployment rate. A negative β_3 would indicate that a one percentage point increase in the unemployment rate would lead to a larger decrease in income or weeks of employment for an obese worker relative to a non-obese worker. This would imply a counter-cyclical effect in which the labor outcome gap between obese and healthy weight workers widens with a percentage point increase in the unemployment rate. On the other hand, a positive β_3 would indicate that obese workers face smaller income or employment penalties than healthy weight workers during recessions. The total differential for obese workers relative to non-obese workers would thus be given by $\beta_1 + \beta_3 * U_{ct}$.

3.2 NLSY Results

In Table 2, I first estimate my baseline specification without occupation fixed effects. Column 1 shows the relationship between the unemployment rate and income is negative, confirming that higher unemployment is associated with lower income for all workers. However, obese workers see an additional 1.1% decrease in income relative to healthy weight workers for every percentage point increase in the unemployment rate. When including occupation fixed effects in column 2, this result remains robust; obese workers face a 1% decrease in income relative to those who are non-obese. This suggests that there is no selection bias for obese workers towards occupations with greater sensitivity to business cycle changes.

To put these findings into perspective, the US unemployment rate increased by about five percentage points over the Great recession. Using my coefficients from column 2, an increase of this magnitude would lead to a 9% decrease in income for all workers, with an additional 5% decrease for obese workers. The mean income of this sample is nearly $24,000. If the unemployment rate increased by 5 percentage points, all workers who earn an income equal to the sample mean would see a decrease of about $2,100. However, obese workers would see an additional loss of over $1,200. These findings indicate that increases in the unemployment rate lead to a counter-cyclical effect in which the income gap between obese and healthy weight workers increases over economic downturns.

It is also important to note the positive, statistically significant coefficient on the obesity dummy variable in my results for the total sample in the first two columns of Table 2. The *positive* effect of obesity on income is driven by black males. The positive coefficient of the obesity dummy on weeks of employment is driven by white and black males. This finding is consistent with some of the previous research in the literature that has found heavier men do better in the labor market. For example, Cawley (2004) finds a positive correlation between weight and education for black males. Moreover, Cawley (2004) also finds overweight white men saw higher wages than white men who were healthy weight.

Table 2: Coefficients for Total Sample: Log of Income and Weeks Employed (NLSY)

	Total Sample		Male		Female	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Log of Income						
Obese * Unemployment Rate	-0.011**	-0.010**	-0.015**	-0.010	-0.014*	-0.018**
	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)
Obese	0.027**	0.030**	0.033**	0.029*	0.010	0.014
	(0.013)	(0.012)	(0.017)	(0.017)	(0.019)	(0.019)
Unemployment Rate	-0.024***	-0.018***	-0.028***	-0.022***	-0.013	-0.009
	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)	(0.009)
R^2	0.376	0.435	0.406	0.467	0.386	0.442
Person-Years	45330	43288	23716	22338	21460	20738
Panel B: Weeks Employed						
Obese * Unemployment Rate	-0.135**	-0.081	-0.213**	-0.195**	-0.173*	-0.043
	(0.061)	(0.056)	(0.088)	(0.081)	(0.091)	(0.079)
Obese	-0.088	0.279**	0.487**	0.715***	-0.864***	-0.217
	(0.156)	(0.138)	(0.226)	(0.194)	(0.236)	(0.213)
Unemployment Rate	-0.644***	-0.317***	-0.875***	-0.422***	-0.356***	-0.164*
	(0.080)	(0.073)	(0.109)	(0.100)	(0.110)	(0.099)
R^2	0.187	0.179	0.225	0.212	0.227	0.204
Person-Years	64629	56941	32005	28555	32469	28187
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Occupation FE		X		X		X

†Standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence and ASVAB test scores. Observations are at the person-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Since the bulk of the previous literature has suggested that the labor market gap between obese and non-obese workers is predominantly driven by females (Averett and Korenmann, 1996; Bhattacharya and Bundorf, 2009; Pagan and Davila, 1997; Caliendo and Lee, 2013; Mason, 2012), I estimate my baseline specification separately by gender. In column 3, income for obese men fall by 1.5% relative to non-obese men. However, column 4 reveals that this result is not robust to occupation fixed effects. This implies that obese men tend to select careers in which income fluctuates relatively more with the business cycle than careers healthy weight men choose. As for females, column 5 shows a percentage point increase in the unemployment rate increases the obesity income gap for women by 1.4%. Including occupation fixed effects in column 6, obese females see an even greater income penalty of 1.8% relative to their non-obese peers. These results confirm findings from the previous literature which suggests that unlike their male counterparts, obese females are more likely to be penalized in the labor market (Averett and Korenmann, 1996; Bhattacharya and Bundorf, 2009; Pagan and Davila, 1997; Caliendo and Lee, 2013; Mason, 2012).

In Panel B I find obese workers do not see statistically significant decreases in weeks employed relative to healthy weight workers when controlling for occupation fixed effects in column 2. When estimating my model separately by gender, I find that obese males see a 0.213 week decrease in the number of weeks employed relative to their non-obese peers. This result is robust to occupation fixed effects in column 4. Results for females in column 5 show a 0.173 decrease in weeks worked relative to healthy weight females. However, this result is not robust to occupation fixed effects, suggesting that obese females are potentially choosing careers in which weeks of employment tend to fluctuate relatively more with the business cycle than careers chosen by non-obese females.

I estimate my baseline specification by race in Table 3. My findings for the total sample are in Panel A. In comparison to their healthy weight counterparts, white workers see a 1.2% decrease in income and a 0.159 decrease in the number of weeks worked relative to non-obese white workers. Moreover, I find workers who are "other race" (that is, those who do not identify as white or black) see a 0.322 decrease in weeks employed relative to their healthier counterparts, but no significant effects for income. There are no statistically significant effects for black workers. I estimate my model by race for males and females in panels B and C respectively. When looking at income, white and black obese men do not see any statistically significant effects. Obese males who are "other race" see a 3% decrease in income relative to their healthy weight counterparts. Columns 4-6 reveal counter-cyclical employment gaps for obese men are driven by white and "other race" workers. For females, panel C shows that the counter-cyclical obesity income gap is driven by white women. Obese white females see a 2.4% decrease in income relative to their non-obese peers. This finding is in line with Cawley (2004) as he finds that weight lowers wages specifically for white females. I find no statistically significant results when using weeks of employment as my dependent variable for all females regardless of race.

Table 3: Coefficients by Race: Log of Income and Weeks Employed (NLSY)

	Log of Income			Weeks Employed		
	White	Black	Other	White	Black	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total Sample						
Obese * Unemployment Rate	-0.012**	-0.007	-0.015	-0.159**	0.088	-0.322*
	(0.005)	(0.012)	(0.012)	(0.074)	(0.104)	(0.167)
Obese	0.018	0.072**	-0.037	0.290	0.643**	-0.665
	(0.015)	(0.028)	(0.041)	(0.184)	(0.282)	(0.479)
Unemployment Rate	-0.026***	-0.019	-0.021	-0.208**	-0.674***	-0.248
	(0.007)	(0.017)	(0.016)	(0.088)	(0.162)	(0.200)
R^2	0.474	0.422	0.500	0.183	0.231	0.251
Person-Years	27602	9784	5640	34536	14488	7665
Panel B: Male						
Obese * Unemployment Rate	-0.009	-0.010	-0.030*	-0.321***	0.016	-0.515**
	(0.007)	(0.016)	(0.018)	(0.101)	(0.168)	(0.242)
Obese	0.025	0.157***	-0.156***	0.549**	2.253***	-1.741**
	(0.020)	(0.046)	(0.056)	(0.255)	(0.464)	(0.675)
Unemployment Rate	-0.023***	-0.013	-0.050**	-0.285**	-0.797***	0.134
	(0.009)	(0.025)	(0.021)	(0.120)	(0.242)	(0.293)
R^2	0.511	0.465	0.573	0.232	0.303	0.311
Person-Years	13139	3983	2575	16616	6177	3567
Panel C: Female						
Obese * Unemployment Rate	-0.024**	-0.008	-0.017	-0.063	0.074	-0.285
	(0.009)	(0.015)	(0.016)	(0.108)	(0.152)	(0.229)
Obese	-0.002	0.019	0.052	0.014	-1.109***	0.146
	(0.025)	(0.042)	(0.066)	(0.281)	(0.406)	(0.707)
Unemployment Rate	-0.028***	0.005	0.026	-0.111	-0.394*	-0.320
	(0.010)	(0.022)	(0.024)	(0.122)	(0.226)	(0.270)
R^2	0.476	0.478	0.525	0.222	0.270	0.300
Person-Years	12726	5157	2651	16484	7733	3755

†Standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence and ASVAB test scores. All estimations control for county, year and occupation fixed effects. Observations are at the person-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.3 BRFSS Empirical Methodology

Using data from the BRFSS, I construct my model as follows:

$$Y_{ist} = \beta_0 + \beta_1 O_{it} + \beta_2 U_{st} + \beta_3 O_{it} * U_{st} + \gamma X_{ist} + \nu_s + \tau_t + \epsilon_{ist}$$

where ist denotes an individual i in state s at time t. Time in this model is the month and year of the interview date. The dependent variable, Y_{ist} denotes the log of the individual's estimated annual income or a dummy variable for employment equal to 1 if the individual is employed at the time of the interview. The variable O_{it} is a dummy for obesity equal to 1 if the individual is obese and 0 otherwise. The variable U_{st} is the de-meaned unemployment rate in percentage points for the month and year of the interview date in individual i's state of residence. The term X_{ist} is a vector of control variables. The terms ν_s and τ_t are state and month-year fixed effects and ϵ_{ist} is the error term. Standard errors are clustered at the state-month level.

3.4 BRFSS Results

Table 4 shows that counter-cyclical obesity income gaps exist for both males and females. In column 1, the obesity income gap widens by 0.2% for the total sample. In columns 2 and 3, the added income differential of obese to non-obese workers over economic downturns is 0.1% for men and women. Columns 4-6 reveal the obesity employment gap also displays a counter-cyclical pattern. For the total sample, obese workers face a 0.2 percentage point decrease in employment in comparison to those who are not obese. By gender, obese males and females face a 0.1 and 0.3 percentage point decrease in employment relative to healthy weight workers respectively.

Table 4: Coefficients for Total Sample: Log of Income and Employment (BRFSS)

	Log of Income			Employment		
	Total Sample	Males	Females	Total Sample	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)
Obese*Unemployment Rate	-0.002***	-0.001**	-0.001***	-0.002***	-0.001**	-0.003***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Obese	-0.073***	-0.020***	-0.103***	-0.007***	-0.005***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Unemployment Rate	-0.013***	-0.013***	-0.013***	-0.009***	-0.011***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
R^2	0.349	0.301	0.381	0.066	0.076	0.062
Person-Months	3703617	1561003	2142614	2911857	1325287	1586570
State FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X

†Standard errors (in parenthesis) are clustered by state-month. Controls include age and it square, female, race, number of children, education and marital status. All estimations include state and month-year fixed effects. Observations are at the person-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5, columns 1-3 display results for income by race. Black workers are the only racial group that do not see any statistically significant income penalties. In column 1, obese white workers see a 0.1% decrease in income while obese “other race” workers see a 0.4% decrease in income relative to their non-obese counterparts. When estimating separately by gender in panels B and C, there are no statistically significant effects for white or black workers. Obese men who are “other race” see a 0.8% decrease in income relative to their healthier counterparts.

In columns 4-6, I estimate my baseline specification with employment as the dependent variable. Counter-cyclical obesity employment gaps are again concentrated amongst white and “other race” workers. Across all panels, the interaction term for white and “other race” workers is negative and statistically significant. In Panel B, obese black men see a *positive*, statistically significant coefficient on the interaction term. This indicates that over economic downturns, obese black men experience a smaller decrease in employment relative to non-obese black men.

Table 5: Coefficients by Race: Log of Income and Employment (BRFSS)

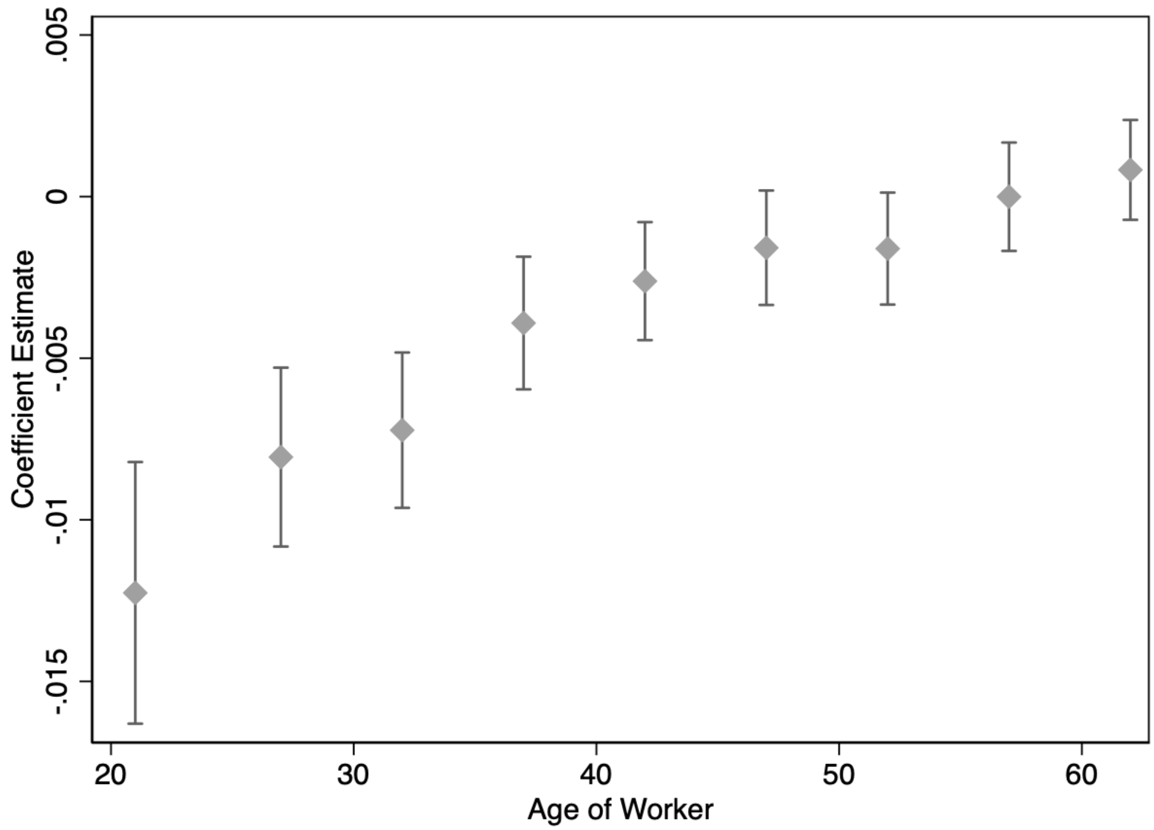
	Log of Income			Employment		
	White	Black	Other	White	Black	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total Sample						
Obese*Unemployment Rate	-0.001***	-0.001	-0.004***	-0.002***	0.001	-0.003***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Obese	-0.078***	-0.042***	-0.063***	-0.007***	-0.002*	-0.009***
	(0.001)	(0.002)	(0.003)	(0.000)	(0.001)	(0.002)
Unemployment Rate	-0.012***	-0.009***	-0.017***	-0.009***	-0.011***	-0.004***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
R^2	0.328	0.319	0.320	0.055	0.097	0.084
Person-Months	3048292	359250	296075	2406703	271731	233423
Panel B: Males						
Obese*Unemployment Rate	-0.001	0.000	-0.008***	-0.001***	0.003***	-0.002**
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
Obese	-0.028***	0.028***	-0.008*	-0.007***	0.006***	-0.005**
	(0.001)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)
Unemployment Rate	-0.012***	-0.008***	-0.017***	-0.010***	-0.013***	-0.005***
	(0.001)	(0.003)	(0.003)	(0.000)	(0.002)	(0.001)
R^2	0.282	0.281	0.286	0.065	0.118	0.099
Person-Months	1300029	125470	135504	1110486	98608	116193
Panel C: Females						
Obese*Unemployment Rate	-0.001	-0.001	-0.001	-0.003***	-0.001	-0.004***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)
Obese	-0.107***	-0.074***	-0.102***	-0.009***	-0.006***	-0.013***
	(0.001)	(0.003)	(0.004)	(0.000)	(0.001)	(0.002)
Unemployment Rate	-0.012***	-0.011***	-0.017***	-0.008***	-0.010***	-0.003***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
R^2	0.362	0.335	0.345	0.051	0.087	0.077
Person-Months	1748263	233780	160571	1296217	173123	117230

†Standard errors (in parenthesis) are clustered by state-month. Controls include age and it square, female, race, number of children, education and marital status. All estimations include state and month fixed effects. Observations are at the person-month level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 Robustness Checks

A key difference in findings between the NLSY and the BRFSS is the magnitude of the interaction term with the log of income as the dependent variable. The coefficient on the interaction term from the NLSY model is about five times as large as the coefficient from the BRFSS. One possible explanation for this discrepancy is the differing age groups in each data set. While the BRFSS sample spans across all working aged adults, the NLSY only includes adults ages 18 to 36. Therefore, the counter-cyclical income gap may only exist for younger obese workers. To test this theory, I run my baseline specification using the BRFSS by 5-year age groups. Figure 1 displays these findings. As predicted, younger, obese workers face the largest income penalties. The obesity income gap for 18-24 year old workers increases by 1.2%, similar to results from the NLSY. As age increases, statistical significance weakens and the magnitude of the effects becomes smaller.

Figure 1: Differential Effects by Age



†The y-axis represents the coefficient for the effect of the interaction between obesity and the unemployment rate on the log of income. The x-axis represents the mean age within a 5-year age group. Standard errors are clustered by state-month. Controls include age and it square, female, race, number of children, education and marital status. All estimations include state and month fixed effects.

I categorized obese individuals in this study based on the CDC's definition for obesity ($BMI \geq 30$). However, given that the cutoff for obesity is quite arbitrary, I estimate my model defining the dummy variable for obesity with differing levels of BMI. Specifically, I create dummy variables for those who have a BMI greater than or equal to various levels ranging from 26 through 40 in 2-unit increments. My coefficient of interest is thus the interaction between the dummy variable (based on differing levels of BMI) and the unemployment rate. In Figure A1, I plot the coefficient of interest from each of my regressions. In all of my estimations, the income gap for obese workers is still counter-cyclical. The income differential for those on the higher end of the BMI spectrum is slightly larger. I repeat this process using data from the BRFSS in Figure A2. My findings from the BRFSS are similar to that of the NLSY. The income differential increases as BMI levels increase. This could imply that those who are more severely obese are subject to greater labor discrimination.

It is possible that larger income losses for obese workers over recessions are not due to employer discrimination, but are instead a reflection of productivity gaps between obese and non-obese workers. In other words, it may be the case that the decrease in income and employment amongst obese workers is due to lower levels of productivity relative to their healthy weight peers. If these cyclical labor outcome gaps are actually due to productivity differences, then we should see the same counter-cyclical income and employment effects amongst obese workers who are self-employed and thus not subject to employer discrimination.

To test this theory, I run my baseline specifications with the NLSY and BRFSS data sets using the log of income as the dependent variable and exclude the samples to self-employed workers. The findings across the NLSY and BRFSS are mixed. In table A1, columns 1-3 show in the NLSY sample there are no statistically significant coefficients on the interaction term for the total sample, males and females. This suggests that over economic downturns, self-employed workers who are obese do not see any differences in income relative to those who are not obese.

Though the results are excluded to a smaller sample size, it is likely that these findings cannot be attributed to a lack of statistical power. If the coefficient of interest was insignificant due to lower statistical power, the results would typically still be negative with much smaller magnitudes. However, columns 1 and 3 show a positive coefficient on the interaction term when estimating for the total sample. These findings are inconsistent with and contradicts my results using the sample of workers who are not self-employed.

I again run my baseline regression restricting the sample to self-employed workers using data from the BRFSS in columns 4-6. My findings from the BRFSS show that obese workers who are self-employed see a 0.2% decrease in income relative to healthy weight self-employed workers for the total sample, significant at the 0.1 level. This could indicate that the counter-cyclical income gap between obese and healthy weight workers is due to a lack of productivity and not employer discrimination. The magnitude of the coefficient is also similar to results for workers who are not self-employed. In columns 5 and 6, results from the BRFSS show no statistically significant counter-cyclical effects for males and females.

While Table A1 displays weak evidence of a lack of productivity driving the counter-cyclical income gap phenomenon in the BRFSS sample, findings from the NLSY suggest that effects are more likely driven by employer discrimination. Taken together, I conclude that employer discrimination is playing at least a partial role in counter-cyclical income effects for the obese, especially in the NLSY sample.

Although the NLSY is an individual level panel, I chose to omit individual fixed effects from my baseline estimation due to attenuation bias caused by measurement error in the county level unemployment rates (Deaton, 1995). Since the BLS estimates unemployment using a time series model based off of a survey of roughly 140,000 businesses and government agencies, it is likely that there is some level of measurement error, especially at smaller geographic levels. However, including individual fixed effects may increase the robustness of my estimates given that it controls for unobserved individual level traits (that is, unobserved ability) that may impact labor outcomes. To this end, I estimate my baseline specification with individual fixed effects using county, state and region level unemployment rates. Table A2 displays my results. In column 1, I find no statistically significant results when using county level unemployment rates in my regression. However, column 2 shows a percentage point increase in the state level unemployment rate leads to a 1% decrease in income for obese workers relative to non-obese workers, significant at the 0.05 level. When using region level unemployment rates in column 3, obese workers face an additional 1.4% decrease in income, significant at the 0.01 level. There are no statistically significant effects when looking at weeks of employment as the dependent variable.

5 Conclusion

The previous literature has shown that discrimination against obese workers leads to a reduction in wages, employment, and other labor outcomes (Cawley, 2004; Pagan and Davila, 1997; Deb et al., 2011; Caliendo and Lee, 2013; Baum and Ford, 2004). These findings are primarily concentrated amongst females (Averett and Korenmann, 1996; Bhattacharya and Bundorf, 2009; Pagan and Davila, 1997; Caliendo and Lee, 2013; Mason, 2012). Though there has been evidence of a direct impact of obesity on labor outcomes (Cawley, 2004; Morris, 2007), none have analyzed the effect of economic downturns on labor market gaps between obese and non-obese workers. This paper contributes new findings to the obesity literature by exploiting the business cycle to estimate the causal impact of obesity on labor outcomes. I find that during economic downturns, the income and employment gaps between obese and healthy weight workers increase, producing a counter-cyclical effect.

Using the NLSY, I find that over economic downturns obese workers see greater income losses than healthy weight workers. These findings are robust to occupation fixed effects suggesting that changes in income differentials are not due to obese workers selecting certain career paths with greater sensitivity to economic downturns. Findings from the NLSY also suggest that counter-cyclical income gaps are predominantly driven by obese females. Looking at the number of weeks of employment as the dependent variable, results from the NLSY show the obesity employment gap widens over economic downturns specifically for males.

Like the NLSY, my results from the BRFSS show that the obesity income gap displays a counter-cyclical pattern for the total sample. When estimating by gender the BRFSS shows both obese men and women see decreases in income relative to their healthy weight peers. My findings from the BRFSS also indicate that obese workers see decreases in employment relative to their non-obese peers over economic downturns, regardless of gender.

While previous studies have proved that obesity can further jeopardize your health (Calle and Thun, 2004; Hossain et al., 2007), this paper contributes to a body of literature that finds obesity also negatively impacts various labor market outcomes. I conclude that worse labor market outcomes for the obese are at least partially driven by employer discrimination. As the obesity rate in the US continues to increase, it is not only imperative to combat the obesity epidemic to decrease negative health impacts, but to also close the labor market gap between obese and healthy weight workers.

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A Appendix

Table A1: Coefficients for Self-Employed Workers: Log of Income

	NLSY			BRFSS		
	Total Sample (1)	Males (2)	Females (3)	Total Sample (4)	Males (5)	Females (6)
Obese*Unemployment Rate	0.001	0.014	-0.015	-0.002*	-0.001	-0.002
	(0.028)	(0.038)	(0.052)	(0.001)	(0.001)	(0.001)
Obese	-0.150*	-0.058	-0.244*	-0.039***	0.001	-0.086***
	(0.086)	(0.117)	(0.148)	(0.002)	(0.003)	(0.003)
Unemployment Rate	-0.048	-0.084	-0.056	-0.015***	-0.016***	-0.014***
	(0.036)	(0.052)	(0.064)	(0.001)	(0.002)	(0.002)
R^2	0.340	0.364	0.443	0.258	0.223	0.313
N	4181	2328	1698	313923	176994	136929

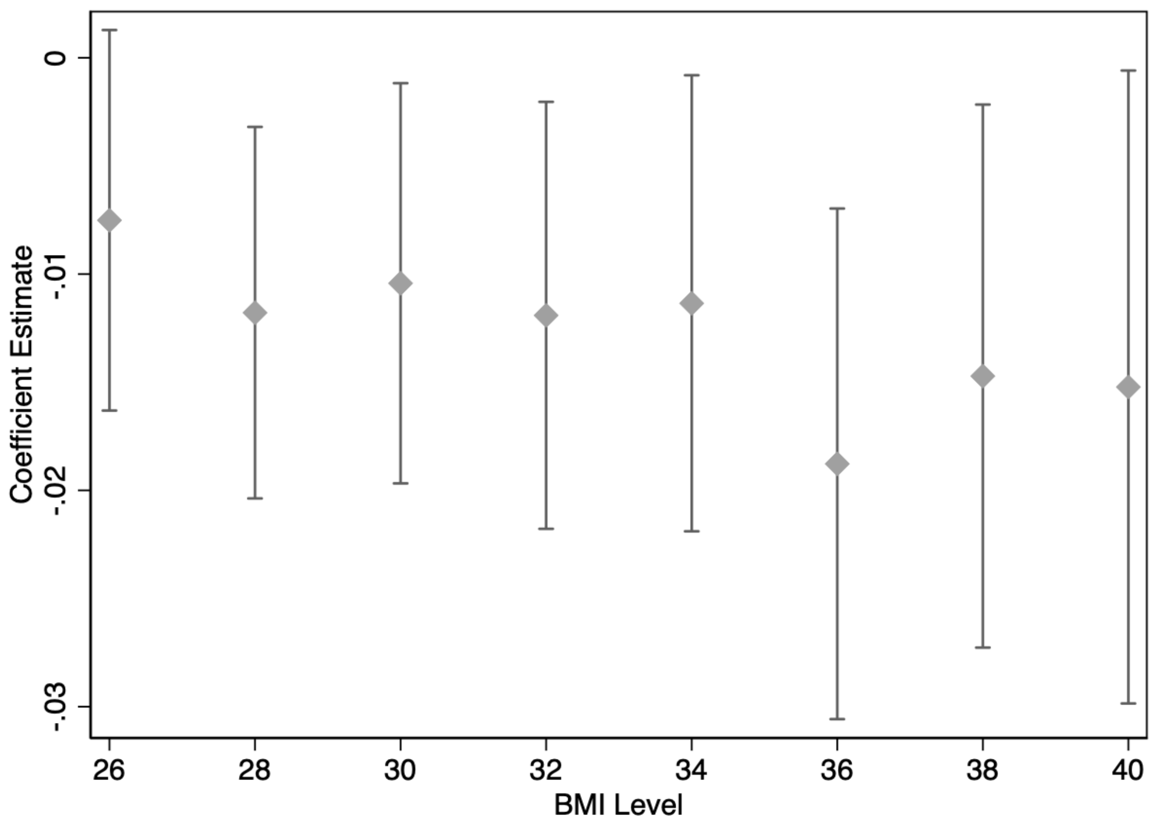
†Standard errors (in parenthesis) by county-year for the NLSY and by state-month for the BRFSS. Controls for the NLSY include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence and ASVAB test scores. Estimations for the NLSY include county and year fixed effects. Controls for the BRFSS include age and it square, female, race, number of children, education and marital status. Estimations for the BRFSS include state and month-year fixed effects. Observations are at the person-year level in the NLSY sample and person-month observations in the BRFSS sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Coefficients Using Individual Fixed Effects with Different Geographic Levels of Unemployment (NLSY)

	Log of Income			Weeks Employed		
	County UR (1)	State UR (2)	Region UR (3)	County UR (4)	State UR (5)	Region UR (6)
Obese * County UR	-0.004			-0.030		
	(0.004)			(0.051)		
County Unemployment Rate	-0.030***			-0.366***		
	(0.005)			(0.067)		
Obese * State UR		-0.010**			-0.056	
		(0.004)			(0.056)	
State Unemployment Rate		-0.025***			-0.271***	
		(0.006)			(0.077)	
Obese * Region UR			-0.014***			-0.077
			(0.005)			(0.061)
Region Unemployment Rate			-0.034**			-0.396**
			(0.014)			(0.178)
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Occupation FE	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X
R^2	0.643	0.634	0.628	0.421	0.410	0.403
Person-Years	51531	51753	51826	69276	69534	69581

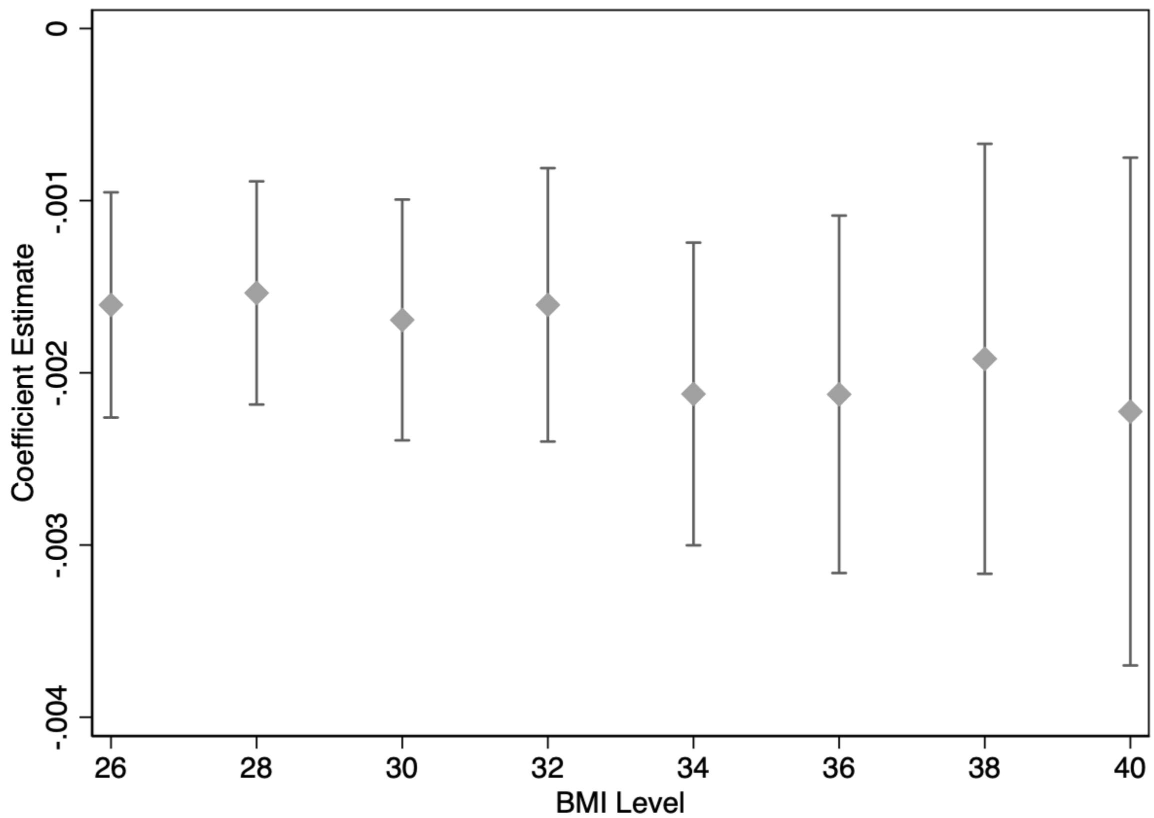
†Standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence, and ASVAB test scores. All estimations include county, year, occupation and individual fixed effects. Observations are at the person-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Differential Effects by BMI Level (NLSY)



†The y-axis represents the coefficient for the effect of the interaction between a dummy variable for obesity (based on different levels of BMI) and the unemployment rate in percentage points. The x-axis represents each BMI level. BMI levels are as follows: $BMI \geq 26$, $BMI \geq 28$, $BMI \geq 30$, $BMI \geq 32$, $BMI \geq 34$, $BMI \geq 36$, $BMI \geq 38$, and $BMI \geq 40$. Standard errors are clustered by county-year. Controls include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence and ASVAB test scores. All estimations include county, year and occupation fixed effects.

Figure A2: Differential Effects by BMI Level (BRFSS)



†The y-axis represents the coefficient for the effect of the interaction between a dummy variable for obesity (based on different levels of BMI) and the unemployment rate in percentage points. The x-axis represents each BMI level. BMI levels are as follows: $BMI \geq 26$, $BMI \geq 28$, $BMI \geq 30$, $BMI \geq 32$, $BMI \geq 34$, $BMI \geq 36$, $BMI \geq 38$, and $BMI \geq 40$. Standard errors are clustered by state-month. Controls include age and it square, female, race, number of children, education and marital status. All estimations include state and month-year fixed effects.