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

by

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Abstract

The obesity epidemic is a growing concern in the United States. Aside from the detrimental health effects of obesity, previous work has also documented a negative relationship between obesity and various labor market outcomes. Given that the American adult obesity rate is roughly 40%, obesity affects a large portion of the US labor market. In this study, I analyze the impact of obesity on income and employment over business cycle fluctuations. I find that during economic downturns, obese workers experience larger declines in income and employment relative to their healthy weight peers. These effects exist for both genders and are concentrated amongst younger adults.

Keywords: obesity, business cycle, discrimination

JEL Classification: J71, I14, E29

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1 Introduction

The obesity epidemic is a growing concern in the United States. According to the Centers for Disease Control and Prevention (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). 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, 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; Moro et al., 2019). However, some have found obesity is negatively associated with labor outcomes for both genders (Baum and Ford, 2004; Morris, 2007; Rooth, 2009). Although previous studies have looked at the relationship between obesity and labor market outcomes, few have been able to establish a causal channel.

In this paper, I present new evidence on how obesity impacts labor market outcomes for workers over the business cycle. While previous research has studied the effects of obesity on various labor market outcomes, none have investigated this relationship over the business cycle. Analyzing the interplay between labor market outcomes, the business cycle, and obesity can shed some insights into employer decisions during economic downturns. To better understand this, I note that that during recessions, the labor supply exceeds the demand for labor, which gives employers greater bargaining power and potentially increases the scope for discrimination.

Although there are several ideas about potential mechanisms behind the obesity penalty, one common explanation is employer discrimination. Discrimination against obese workers has been documented in laboratory settings by sociologists since 1979 (Larkin and Pines, 1979;

[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.

Roehling, 1999; Rooth, 2009). Although a large portion of the adult population is overweight or obese, there is still a stigma attached to heavier 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.

Aside from discrimination, those who are obese are more susceptible to various health conditions which may lower productivity in the workplace (Calle and Thun, 2004; Hossain et al., 2007). Gates et al. (2008) finds workers who are moderately or severely obese experience a 4.2% health-related loss in productivity, 1.18% more than all other workers. Moreover, Sullivan et al. (2008) finds that while chronic illnesses such as diabetes and hypertension lowers productivity for healthy weight workers, obesity further exacerbates its effects.[2] For these reasons, in a recession employers may be more likely to lay off obese workers due to lower levels of productivity. Taken together, we could expect labor market gaps between obese and non-obese workers to widen during economic downturns.

Using the National Longitudinal Survey of Youth (NLSY) as in Baum and Ford (2004), I follow the empirical strategy of Biddle and Hamermesh (2013) to test whether labor market penalties are larger for obese workers over economic downturns. I provide additional evidence of these labor market penalties using data from the Behavioral Risk Factor Surveillance System (BRFSS). Although 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 business cycle fluctuations impact these differentials.

I find that during economic downturns obese workers face larger declines in income and employment outcomes than their non-obese peers. These effects exist for both genders and are concentrated amongst younger workers who are likely at earlier stages of their careers and thus have less bargaining power. My results are not influenced by selection bias in which obese

[2] See Hammond and Levine (2010) for a review of the impact of obesity on productivity.

workers tend to choose careers that fluctuate relatively more with unemployment. Finally, I find that the effects are at least partially driven by productivity gaps between obese and healthy weight workers.

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. I use the NLSY's geocode data which reports each individuals county of residence during each interview round. This study uses data from the years 2000-2011, 2013 and 2015. I eliminate 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 earning zero dollars for the year. Thus, I set income for these individuals as one dollar before taking the log.

2.2 Behavioral Risk Factor Surveillance System

To supplement my results from the NLSY, I also use data from the Behavioral Risk Factor Surveillance System (BRFSS), an epidemiological surveillance survey sponsored by the Centers for Disease Control and Prevention (CDC) and other federal agencies. The data is a repeated cross-section survey established in 1984 that interviews roughly 400,000 American adults annually. Although the BRFSS is less comprehensive than the NLSY, the data has a much larger sample size. Thus, exploiting both the NLSY and the BRFSS provides added robustness.

To keep my results consistent with the NLSY, I use survey data from the years 2000-2018. The BRFSS asks individuals to report their household income within one of eight possible income brackets. I code household 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 adults who are over the 30-34 year old age bracket to align the age range of the BRFSS sample with the NLSY. Thus, individuals in the BRFSS sample are ages 18 to 34 years old. Although I eliminate adults over 34 years old, I exploit the wider age range of the BRFSS later in this study to assess differential effects by age group.

2.3 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 various geographic levels. The data is originally collected from the Current Employment Statistics, a monthly survey conducted by the BLS. The survey sample size includes approximately 122,000 businesses and government agencies. For the NLSY and BRFSS, I use the unemployment rate at the county-year level and state-month level, respectively.

2.4 Summary Statistics

In both data sets, I calculate each individual's body mass index (BMI) using their self-reported height and weight.[3] 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 consid-

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

ered obese if they have 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." Finally, I remove active members of the armed forces.

Table 1 displays summary statistics for both the NLSY and BRFSS. Among those in the NLSY sample, the mean annual income is roughly $24,000 per year (in nominal US dollars). Moreover, 28% of individuals have college degrees, 25% are married and the average number of weeks employed in a year is roughly 44 weeks. With a mean age of about 25 years old, these statistics represent characteristics of a young adult working population. Like the NLSY, the BRFSS also consists of younger workers with a mean age of roughly 28 years old. 66% of the sample individuals attended college for at least one year and 46% are married. The mean annual household income is about $43,000 (in nominal US dollars) and 90% of the sample was employed at the time of their interview.

BMI statistics are similar across the NLSY and the BRFSS. In both data sets, the mean sample BMI is roughly 26, indicating that the average individual is overweight by definition according to the CDC. The individuals in the NLSY weigh slightly more on average and have a higher obesity rate of 25%. In comparison, 22% of individuals in the BRFSS are obese.

3 Empirical Methodology

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:

$$Y_{ilt} = \beta_0 + \beta_1 O_{it} + \beta_2 U_{lt} + \beta_3 O_{it} * U_{lt} + \gamma X_{ilt} + \nu_l + \tau_t + \epsilon_{ilt}$$

Using the NLSY, Y_{ilt} denotes the log of income or number of weeks worked for individual i living in county l 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_{lt}, is the de-meaned annual unemployment rate reported in percentage points at the county level. The term X_{ilt} is a vector of controls including marital status, age and its square, gender, education level, race, number of children, an urban residence indicator, and ASVAB test scores.[4] The terms ν_l and τ_t denote county and year fixed effects respectively. Standard errors are clustered at the county-year level.

I implement a similar specification using data from the BRFSS where Y_{ilt} denotes the log of annual household income or a dummy variable equal to 1 if individual i was employed in state l during the survey month and year t. My vector of covariates, X_{ilt} include gender, age and its square, years of education, race, marital status, and number of children. The terms ν_l and τ_t denote state and interview month fixed effects respectively. I cluster standard errors by state-month.

Theoretically, the NLSY model could include individual fixed effects since the data is an individual level panel. However, the results produced by the regression would have to rely on workers who significantly alter their BMI or move across counties during the sample period. The remaining variation in the unemployment rate would likely not be conducive to this study since most workers who move across counties do so in search of better job opportunities. Furthermore, since the BLS estimates unemployment using a relatively small sample size of establishments, there exists some degree of measurement error especially at the county level. Including individual fixed effects would further exacerbate the attenuation bias.[5] To this end, I choose to omit individual fixed effects from my main specification. However, I later run my

[4] To reduce 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 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.

[5] 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."

regression with individual fixed effects as a robustness check in the appendix.

The term, β_1, is interpreted as the average effect of obesity on income or employment outcomes. 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 employment outcomes 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. In contrast, 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 $\beta_1 + \beta_3 * U_{lt}$.

4 Results

4.1 Baseline Results

I estimate my baseline specification in Table 2. Focusing on the NLSY sample in Panel A, a percentage point increase in the unemployment rate decreases income for all workers by 2.4%. Obese workers face an additional 1.5% income penalty. Looking at the results by gender in columns 2 and 3, both obese men and women face larger decreases than their non-obese peers with additional income penalties of 1.7% and 2.1% respectively. Results from the BRFSS in Panel B are similar. For the total sample, income penalties for obese workers are 0.8% larger than their healthy weight peers. Moreover, findings in columns 2 and 3 also indicate that the obesity penalty grows with unemployment for both genders.

In columns 4 through 6 I estimate my baseline specification with employment outcomes as the dependent variable. For the total sample, results from the NLSY indicate that increases in unemployment lead to larger decreases in weeks of employment for the obese. However, there are no statistically significant counter-cyclical effects for obese women. Results from the BRFSS in Panel B show economic downturns lead to larger declines in employment for the obese. However, when estimating my baseline specification by gender, the obesity penalty for employment grows during downturns for females only.

To put these findings into perspective, the US unemployment rate increased by about five percentage points over the Great recession. Using my findings from the NLSY in column 1, an increase of this magnitude would lead to a 12% decrease in income for all workers, with an additional 7.5% decrease for obese workers. The mean income of this sample is roughly $24,000. If the unemployment rate increased by five percentage points, all workers who earn $24,000 per year would see a decrease of $2,880. Obese workers would see an additional loss of $1,800.

It is also important to note the point estimates on the obesity dummy variable in my main results. In columns 1 and 2, (although it is not statistically significant) there is a positive relationship between obesity and income. Moreover, column 5 shows a positive, statistically significant relationship between obesity and weeks of employment for males. These positive relationships are driven by black and white men. This finding is consistent with 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 and also finds overweight white men receive higher wages than their healthier peers. In contrast, point estimates for the obesity dummy variable are negative and statistically significant across both genders using data from the BRFSS. Point estimates for obesity are more akin to that of Baum and Ford (2004). Using an OLS model with individual fixed effects, they find that obesity is associated with roughly a 3% decrease in wages for men and a 6% decrease for women.

4.2 Differential Effects by Racial Group

I estimate my baseline specification by race in Table 3. My findings for the total sample are displayed in Panel A. There are no statistically significant effects by race when using the log of income as my dependent variable. Workers who are "other race" (that is, those who do not identify as white or black) face larger decreases in weeks of employment than their non-obese peers. I estimate my model by race for males and females in panels B and C respectively. The results in panel B indicate that obese black and "other race" men face larger labor market penalties during recessions than their non-obese peers. For females, panel C shows that the obesity income penalty is driven by white women. This finding is in line with Cawley (2004) as he finds that weight lowers wages specifically for white females. Employment effects are driven by "other race" females.

I also estimate my baseline specification by race using data from the BRFSS in Table 4. Looking at household income as the dependent variable, obese workers face larger decreases in their income over recessions regardless of race for the total sample and for males. For females, the obesity income penalty grows during downturns for white and black women. With employment as the dependent variable, Columns 4-6 show employment effects are driven by white and black workers for the total sample. There are no statistically significant effects on employment for males. However, findings for females show the obesity employment penalty increases during downturns for white women.

4.3 Differential Effects by Age

While the main findings of this study focuses on young adults who are at earlier stages of their careers, it may be interesting to look at differential effects for working adults across a wider array of age groups. I exploit data from the BRFSS and regress my baseline specification using a wider range of working aged adults (ages 18 through 64) years old. Table A1 displays my findings. the coefficients on the interaction term are smaller than my main results from Table

2 which uses the sample of younger workers. This indicates that the effects could be driven by younger workers. To test this theory, I regress my main specification in 5-year age buckets. I display my results in Figure A1. The obesity income gap for the youngest age group (18-24 years old) increases by 1.1% for every percentage point increase in the unemployment rate. As age increases, statistical significance weakens and the magnitude of the effects becomes smaller. This implies that my findings are driven by younger workers.

5 Robustness Checks

5.1 Measurement Error in Self-Reported Body Weight

Self-reported weight could potentially include some degree of misreporting error which may lead to biased estimates (Judge, 1985; O'Neill and Sweetman, 2013). In order to correct for this, I exploit data from the National Health and Nutrition Examination Survey (NHANES) for the years 2000-2017.[6] A unique feature of this data 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 create imputed values of body weight using coefficients from the regression. I use these imputed body weight values to calculate each individual's BMI in the NLSY and the BRFSS and estimate my baseline specification in Table A2. I find that the results are similar to my findings which use raw values of self-reported body weight. Therefore, measurement error in self-reported weight does not affect my results.

[6]The NHANES is a program conducted by the CDC that assesses the health and nutritional status of US adults and youths.

5.2 Occupation Bias

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 differentials would widen when the unemployment rate increases due to career choice and not discrimination against the obese. Including occupation fixed effects mitigates this potential selection bias.

Using data from the NLSY, I estimate my baseline specification with occupation fixed effects in Table A3. With log of income as the dependent variable in columns 1-3, the results remain relatively similar to Table 2. Obese men and women face larger decreases in income than their non-obese peers during recessions. Employment effects are slightly weaker. Obese men face larger declines in their weeks of employment during economic downturns than their healthier peers. Results for females and for the total sample are not statistically significant.

5.3 Productivity vs Employer Discrimination

It is possible that larger labor market gaps over recessions are not due to employer discrimination, but instead reflect productivity differences between obese and non-obese workers. In this case, recessions act as a "survival of the fittest" test in which employers lay off or reduce wages for their least productive employees. If my findings are due to employer discrimination rather than productivity, then we should see larger negative effects for obese workers who are firm-employed since self-employed workers are not subject to employer discrimination (because they are their own employer).

To test this theory, I employ a modification of my baseline specification using a triple interaction to estimate the differential effect between obese workers who are firm-employed versus self-employed. The estimated coefficient on the triple interaction between a dummy variable for firm-employment, a dummy variable for obesity and the unemployment rate measures the added penalty that obese, firm-employed workers experience over self-employed obese workers. In Table A4, coefficients on the triple interaction term for both the NLSY and the BRFSS are not statistically significant. Obese workers who are firm employed do not face any additional penalties relative to their self-employed counterparts, suggesting there may not be an employer bias. While self-employed workers do not have employers, they could still be subject to some bias if clients choose not to work with heavier workers due to their discriminatory preferences. Thus, discrimination could still be at work.

To this end, I conduct another test to see if my baseline results are due to productivity differences instead of discrimination. One explanation of why obese workers may be less productive is because they are more likely to have health issues that limit their work. Thus, as an added robustness check I follow Baum and Ford (2004) and include a control for whether an individual is limited in their job due to their health. If the coefficient of interest becomes statistically insignificant, this could potentially indicate that the effect of obesity on labor market outcomes during downturns is instead due to health limitations that reduce productivity. I display my results in Table A5. The coefficient of interest is no longer statistically significant for both log of income and weeks of employment as the dependent variable. This suggests the added labor market penalty during recessions for obese workers may be driven by their weaker levels of productivity. However, it is important to note that data on health limitations during work is only available for the years 2007 to 2010, 2013 and 2015. This cuts the sample period by more than half thus reducing statistical power. Taken together, my findings indicate that productivity plays at least a partial role in cyclical labor market differentials between obese and non-obese workers.

5.4 Definition of Obesity

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 replacing the dummy variable for obesity with other BMI cutoffs. Specifically, I create dummy variables for those who have a BMI greater than or equal a range of 26 through 40 in 2-unit increments. My coefficient of interest is thus the interaction between the dummy variable (based on various levels of BMI) and the unemployment rate. In Figure A2, I plot the coefficient of interest from each of my regressions using the NLSY. 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 A3. My findings from the BRFSS are similar to that of the NLSY. The income differential increases as BMI levels increase.

5.5 Individual Fixed Effects

Although I chose to omit individual fixed effects from my model using the NLSY, including them 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 regional unemployment rates. Table A6 displays my results. Using county level unemployment in my model, I find no statistically significant results. However, using state and regional unemployment rates, the obesity penalty on income grows as unemployment increases.

5.6 Estimates for Various Time Periods

Because the US obesity rate has been rising steadily since the beginning of the sample period, obesity may be perceived as more common and thus stigmas attached to obese workers may have changed over time. This could also lead to changes in labor market outcomes for the obese over time. To analyze this, I split my sample into three time periods (2000 to 2004, 2005 to 2009, and 2010 to the end of the sample period) and estimate my main specification. I display my findings in Table A7. Using data from the NLSY, obese workers face a larger decrease in income relative to their healthier peers for the 2005-2009 time period. Results from the BRFSS shows the obesity income penalty increases with unemployment for the 2005 to 2009 and 2010 to 2018 time periods. There are no statistically significant employment outcomes across both data sets. However, the statistical significance of the coefficients could be attributed to the differences in sample sizes for each regression.

6 Conclusion

The previous literature has shown that obesity has a negative effect on wages, employment, and other labor outcomes (Cawley, 2004; Pagan and Davila, 1997; Deb et al., 2011; Caliendo and Lee, 2013; Baum and Ford, 2004). While 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), a number of other studies have also found that obesity negatively impacts both genders (Baum and Ford, 2004; Morris, 2007; Rooth, 2009). Although 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.

Using data from the NLSY, I find that during recessions obese workers face larger declines in labor market outcomes than their healthy weight peers. My findings from the BRFSS support these results. Moreover, these effects are primarily driven by younger workers. Using the BRFSS, I find that penalties for obesity are largest for the youngest age group (ages 18 through 24). As age increases, the obesity penalty becomes smaller. Furthermore, I find that my effects are not driven by selection bias in which obese workers tend to select careers that fluctuate relatively more with the unemployment rate.

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 while employer discrimination may be at play, worse labor market outcomes for the obese are at least partially driven by lower levels of productivity. As the obesity rate in the US continues to increase, it is not only imperative to mitigate the negative health impacts of obesity, but also the labor market effects.

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Table 1: Summary Statistics

	NLSY		BRFSS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.48	0.50	0.53	0.50
Age	25.23	4.27	27.76	4.32
Height (in.)	67.86	4.17	67.56	4.14
Weight (lbs.)	177.24	46.33	173.34	43.37
Body Mass Index (BMI)	26.96	6.30	26.58	5.78
Obese	0.25	0.43	0.22	0.41
Annual Income	24182.44	23661.08		
Annual Household Income			44317.81	22477.26
Weeks Employed Per Year	44.21	13.84		
Employed			0.90	0.30
Unemployment Rate	6.34	2.49	6.02	2.07
College Degree	0.28	0.45		
Attended College			0.66	0.47
White	0.65	0.48	0.77	0.42
Black	0.22	0.41	0.11	0.32
Other Race	0.13	0.34	0.11	0.31
Number of Children	0.53	0.93	1.11	1.23
Married	0.25	0.43	0.46	0.50
Urban Residence	0.80	0.40		
ASVAB Test Scores	50589.48	28677.63		
	N=6563		NT=403360	

†*Sources: National Longitudinal Surveys, Bureau of Labor Statistics. Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* Data from the NLSY uses survey waves 2000-2013, 2015 and 2017. Data from the BRFSS uses survey waves 2000-2018. Annual income and annual household 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.

Table 2: Effect of Obesity on Labor Market Outcomes Over the Business Cycle

	Total Sample (1)	Males (2)	Females (3)	Total Sample (4)	Males (5)	Females (6)
Panel A: NLSY	Log of Income			Weeks Employed		
Obese * Unemployment Rate	-0.015***	-0.017**	-0.021***	-0.127**	-0.212**	-0.148
	(0.005)	(0.007)	(0.008)	(0.061)	(0.086)	(0.093)
Obese	0.018	0.027	-0.007	-0.088	0.448**	-0.913***
	(0.013)	(0.018)	(0.020)	(0.155)	(0.220)	(0.236)
Unemployment Rate	-0.024***	-0.028***	-0.013	-0.561***	-0.732***	-0.317***
	(0.006)	(0.008)	(0.009)	(0.076)	(0.101)	(0.104)
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.338	0.356	0.358	0.180	0.217	0.217
Person-Years	50397	26641	23604	71515	35811	35554
Panel B: BRFSS	Log of Household Income			Employment		
Obese * Unemployment Rate	-0.008***	-0.006***	-0.008***	-0.003***	-0.001	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Obese	-0.094***	-0.034***	-0.131***	-0.014***	-0.013***	-0.017***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Unemployment Rate	-0.016***	-0.016***	-0.017***	-0.010***	-0.012***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Controls	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
R^2	0.252	0.186	0.302	0.077	0.084	0.078
Person-Months	819120	370993	448127	444941	209377	235564

†*Sources: National Longitudinal Surveys, Bureau of Labor Statistics. Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* For the NLSY regressions in Panel A, standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, gender, race, highest degree obtained, number of children, marital status, urban residence and ASVAB test scores. For the BRFSS regressions in Panel B, standard errors (in parenthesis) are clustered by state-month. Controls include gender, age and its square, race, education, marital status, and number of children. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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	-0.009	-0.017	-0.014	-0.098	-0.031	-0.457***
	(0.006)	(0.012)	(0.011)	(0.084)	(0.120)	(0.163)
Obese	0.024	0.027	-0.056	-0.114	0.280	-0.710
	(0.016)	(0.030)	(0.040)	(0.200)	(0.303)	(0.475)
Unemployment Rate	-0.032***	-0.030*	-0.032*	-0.487***	-0.877***	-0.743***
	(0.007)	(0.016)	(0.017)	(0.088)	(0.161)	(0.196)
R^2	0.371	0.323	0.372	0.170	0.225	0.198
Person-Years	32345	11407	6730	42504	19335	9860
Panel B: Male						
Obese * Unemployment Rate	-0.002	-0.032*	-0.033**	-0.126	-0.019	-0.578***
	(0.008)	(0.018)	(0.015)	(0.109)	(0.188)	(0.227)
Obese	0.042**	0.076*	-0.110**	0.324	2.596***	-2.488***
	(0.021)	(0.045)	(0.048)	(0.281)	(0.453)	(0.650)
Unemployment Rate	-0.035***	-0.020	-0.066***	-0.641***	-1.031***	-0.776***
	(0.009)	(0.024)	(0.022)	(0.117)	(0.226)	(0.277)
R^2	0.401	0.325	0.396	0.197	0.275	0.240
Person-Years	17585	5489	3590	21758	9174	4921
Panel C: Female						
Obese * Unemployment Rate	-0.030***	-0.013	0.010	-0.168	-0.133	-0.462**
	(0.010)	(0.017)	(0.017)	(0.133)	(0.171)	(0.231)
Obese	0.007	-0.025	0.007	-0.619*	-1.815***	1.050
	(0.026)	(0.042)	(0.063)	(0.328)	(0.420)	(0.720)
Unemployment Rate	-0.024**	-0.025	0.002	-0.292**	-0.485**	-0.577**
	(0.011)	(0.022)	(0.025)	(0.123)	(0.225)	(0.280)
R^2	0.388	0.387	0.403	0.239	0.257	0.261
Person-Years	14610	5862	3108	20597	10112	4904

†*Source: National Longitudinal Surveys, Bureau of Labor Statistics.* 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 and year fixed effects. Observations are at the person-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Coefficients by Race: Log of Income and Employment (BRFSS)

	Log of Income			Employment		
	White (1)	Black (2)	Other (3)	White (4)	Black (5)	Other (6)
Panel A: Total Sample						
Obese * Unemployment Rate	-0.007***	-0.010***	-0.007*	-0.002**	-0.003*	-0.004
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
Obese	-0.100***	-0.060***	-0.074***	-0.016***	-0.002	-0.019***
	(0.002)	(0.005)	(0.005)	(0.001)	(0.004)	(0.004)
Unemployment Rate	-0.016***	-0.009*	-0.014***	-0.009***	-0.011***	-0.005*
	(0.002)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)
R^2	0.224	0.256	0.241	0.063	0.099	0.077
Person-Months	636655	88334	94131	342538	51680	50723
Panel B: Males						
Obese * Unemployment Rate	-0.006**	-0.012**	-0.011*	-0.001	-0.003	-0.005
	(0.002)	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)
Obese	-0.039***	0.005	-0.020*	-0.015***	0.013*	-0.016**
	(0.003)	(0.009)	(0.008)	(0.002)	(0.006)	(0.006)
Unemployment Rate	-0.016***	-0.005	-0.014***	-0.013***	-0.005	-0.008**
	(0.002)	(0.006)	(0.004)	(0.001)	(0.004)	(0.003)
R^2	0.165	0.188	0.200	0.070	0.119	0.099
Person-Months	294825	31118	45048	166223	17885	25268
Panel C: Females						
Obese * Unemployment Rate	-0.007***	-0.008**	-0.004	-0.003**	-0.004	-0.003
	(0.002)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)
Obese	-0.142***	-0.084***	-0.116***	-0.018***	-0.010**	-0.023***
	(0.003)	(0.006)	(0.008)	(0.002)	(0.004)	(0.006)
Unemployment Rate	-0.016***	-0.011*	-0.014**	-0.006***	-0.015***	-0.002
	(0.002)	(0.005)	(0.005)	(0.001)	(0.003)	(0.003)
R^2	0.277	0.283	0.275	0.063	0.094	0.071
Person-Months	341830	57215	49082	176315	33795	25454

†*Source: Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

Table A1: Coefficients for All Age Groups (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*	-0.001***	-0.001	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Obese	-0.073***	-0.020***	-0.107***	-0.009***	-0.008***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment Rate	-0.012***	-0.013***	-0.013***	-0.009***	-0.010***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
R^2	0.344	0.293	0.379	0.051	0.062	0.047
N	3799284	1650496	2148788	1884405	824183	1060222

†*Source: Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Coefficients Using Adjusted Body Weight

	Total Sample (1)	Males (2)	Females (3)	Total Sample (4)	Males (5)	Females (6)
Panel A: NLSY	Log of Income			Weeks Employed		
Obese*Unemployment Rate	-0.014***	-0.017**	-0.019**	-0.132**	-0.222***	-0.153*
	(0.005)	(0.007)	(0.008)	(0.061)	(0.086)	(0.089)
Obese	0.020	0.029	-0.001	-0.088	0.455**	-0.822***
	(0.013)	(0.018)	(0.020)	(0.154)	(0.219)	(0.231)
Unemployment Rate	-0.024***	-0.028***	-0.013	-0.556***	-0.729***	-0.310***
	(0.006)	(0.008)	(0.009)	(0.076)	(0.102)	(0.104)
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.338	0.356	0.358	0.180	0.217	0.217
Person-Years	50397	26641	23604	71515	35811	35554
Panel B: BRFSS	Log of Household Income			Employment		
Obese*Unemployment Rate	-0.008***	-0.006***	-0.008***	-0.002***	-0.001	-0.004***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Obese	-0.093***	-0.033***	-0.127***	-0.014***	-0.013***	-0.016***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
Unemployment Rate	-0.016***	-0.016***	-0.016***	-0.010***	-0.012***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Controls	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
R^2	0.253	0.186	0.302	0.077	0.084	0.078
Person-Months	819120	370993	448127	444941	209377	235564

†*Sources: National Longitudinal Surveys, Bureau of Labor Statistics. Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* For the NLSY regressions in Panel A, 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. For the BRFSS regressions in Panel B, standard errors (in parenthesis) are clustered by state-month. Controls include gender, age and is square, race, education, marital status, and number of children. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Coefficients Using Occupation Fixed Effects (NLSY)

	Log of Income			Weeks Employed		
	Total Sample	Males	Females	Total Sample	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)
Obese * Unemployment Rate	-0.014***	-0.014**	-0.024***	-0.074	-0.180**	-0.038
	(0.005)	(0.006)	(0.007)	(0.052)	(0.072)	(0.079)
Obese	0.021*	0.026	0.003	0.265**	0.706***	-0.333
	(0.012)	(0.017)	(0.020)	(0.132)	(0.186)	(0.204)
Unemployment Rate	-0.018***	-0.023***	-0.007	-0.265***	-0.348***	-0.128
	(0.006)	(0.008)	(0.009)	(0.065)	(0.089)	(0.089)
Controls	X	X	X	X	X	X
Occupation FE	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.391	0.407	0.414	0.173	0.208	0.196
Person-Years	48301	25223	22873	63687	32281	31220

†*Source: National Longitudinal Surveys, Bureau of Labor Statistics.* 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Coefficients for Firm Employed Workers

	NLSY (1)	BRFSS (2)
Obese * Unemployment Rate * Firm-Employed	0.033	0.004
	(0.026)	(0.004)
Obese * Unemployment Rate	–0.045*	–0.008*
	(0.026)	(0.004)
Obese * Firm-Employed	0.094	–0.002
	(0.061)	(0.008)
Unemployment Rate * Firm-Employed	0.008	0.015***
	(0.012)	(0.002)
Obese	–0.068	–0.056***
	(0.060)	(0.008)
Unemployment Rate	–0.030**	–0.029***
	(0.013)	(0.003)
Firm-Employed	0.306***	0.040***
	(0.030)	(0.004)
Controls	X	X
County FE	X	
Year FE	X	
State FE		X
Month FE		X
R^2	0.343	0.304
N	50397	400889

†*Sources: National Longitudinal Surveys, Bureau of Labor Statistics. Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* For the NLSY regressions, standard errors (in parenthesis) are clustered by county-year. N is the number of observations in person-years. Controls include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence, and ASVAB test scores. For the BRFSS regressions, standard errors (in parenthesis) are clustered by state-month. N is the number of observations in person-months. Controls include gender, age and its square, race, education, marital status, and number of children. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Coefficients With Work Limitations Control (NLSY)

	Log of Income			Weeks Employed		
	Total Sample	Males	Females	Total Sample	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)
Obese * Unemployment Rate	-0.007	-0.012	-0.010	-0.127	-0.175	-0.140
	(0.007)	(0.008)	(0.011)	(0.081)	(0.115)	(0.121)
Obese	0.021	0.029	-0.004	0.297	0.465	-0.564
	(0.018)	(0.025)	(0.028)	(0.221)	(0.301)	(0.353)
Unemployment Rate	-0.008	-0.013	0.002	-0.128	-0.282**	0.078
	(0.009)	(0.013)	(0.012)	(0.099)	(0.132)	(0.148)
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.195	0.213	0.250	0.239	0.271	0.290
Person-Years	23738	12593	10999	31098	15555	15394

†*Source: National Longitudinal Surveys, Bureau of Labor Statistics.* Standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, gender, race, highest degree obtained, number of children, marital status, urban residence, ASVAB test scores and an indicator if the individual reports being limited in work due to their health. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: 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	-0.006			-0.043		
	(0.005)			(0.058)		
County Unemployment Rate	-0.030***			-0.539***		
	(0.006)			(0.077)		
Obese * State UR		-0.012**			-0.107	
		(0.005)			(0.065)	
State Unemployment Rate		-0.023***			-0.517***	
		(0.007)			(0.089)	
Obese * Region UR			-0.013**			-0.109
			(0.006)			(0.070)
Region Unemployment Rate			-0.043**			-0.624***
			(0.017)			(0.206)
Obese	-0.015	-0.014	-0.013	-0.318	-0.314	-0.312
	(0.018)	(0.018)	(0.018)	(0.210)	(0.210)	(0.210)
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X
R^2	0.591	0.590	0.590	0.495	0.494	0.494
Person-Years	50026	50052	50051	71366	71419	71418

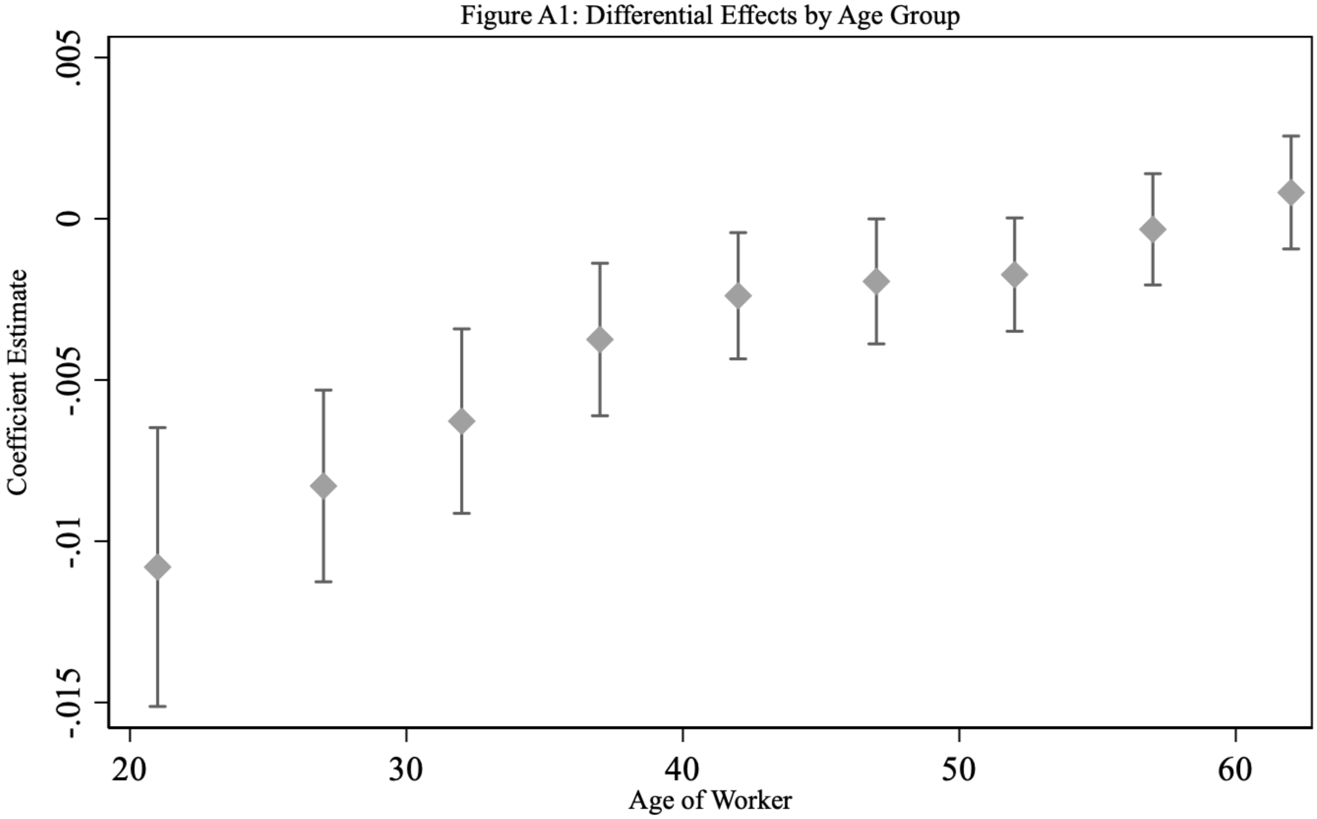
†*Source: National Longitudinal Surveys, Bureau of Labor Statistics.* Standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, female, race, highest degree obtained, number of children, marital status, urban residence, and ASVAB test scores. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Coefficients by Time Period

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: NLSY	Log of Income			Weeks Employed		
	2000-2004	2005-2009	2010-2017	2000-2004	2005-2009	2010-2017
Obese * Unemployment Rate	-0.014	-0.015*	-0.011	-0.234	-0.090	-0.147
	(0.018)	(0.009)	(0.008)	(0.177)	(0.112)	(0.099)
Obese	0.017	-0.005	0.028	-0.281	0.068	-0.325
	(0.033)	(0.023)	(0.022)	(0.333)	(0.263)	(0.308)
Unemployment Rate	-0.035*	-0.015	0.001	-0.603***	-0.420***	-0.050
	(0.020)	(0.011)	(0.011)	(0.223)	(0.132)	(0.130)
Controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
R^2	0.256	0.190	0.206	0.174	0.191	0.215
Person-Years	14952	19127	15939	24184	26070	20898
Panel B: BRFSS	Log of Household Income			Employment		
	2000-2004	2005-2009	2010-2018	2000-2004	2005-2009	2010-2018
Obese * Unemployment Rate	-0.006	-0.007***	-0.007***	-0.000	-0.001	-0.001
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Obese	-0.082***	-0.100***	-0.093***	-0.014***	-0.011***	-0.018***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Unemployment Rate	-0.002	-0.017***	-0.008***	-0.009***	-0.011***	-0.007*
	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)
Controls	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
R^2	0.253	0.292	0.235	0.051	0.079	0.090
Person-Months	186592	221918	410610	151401	175593	117947

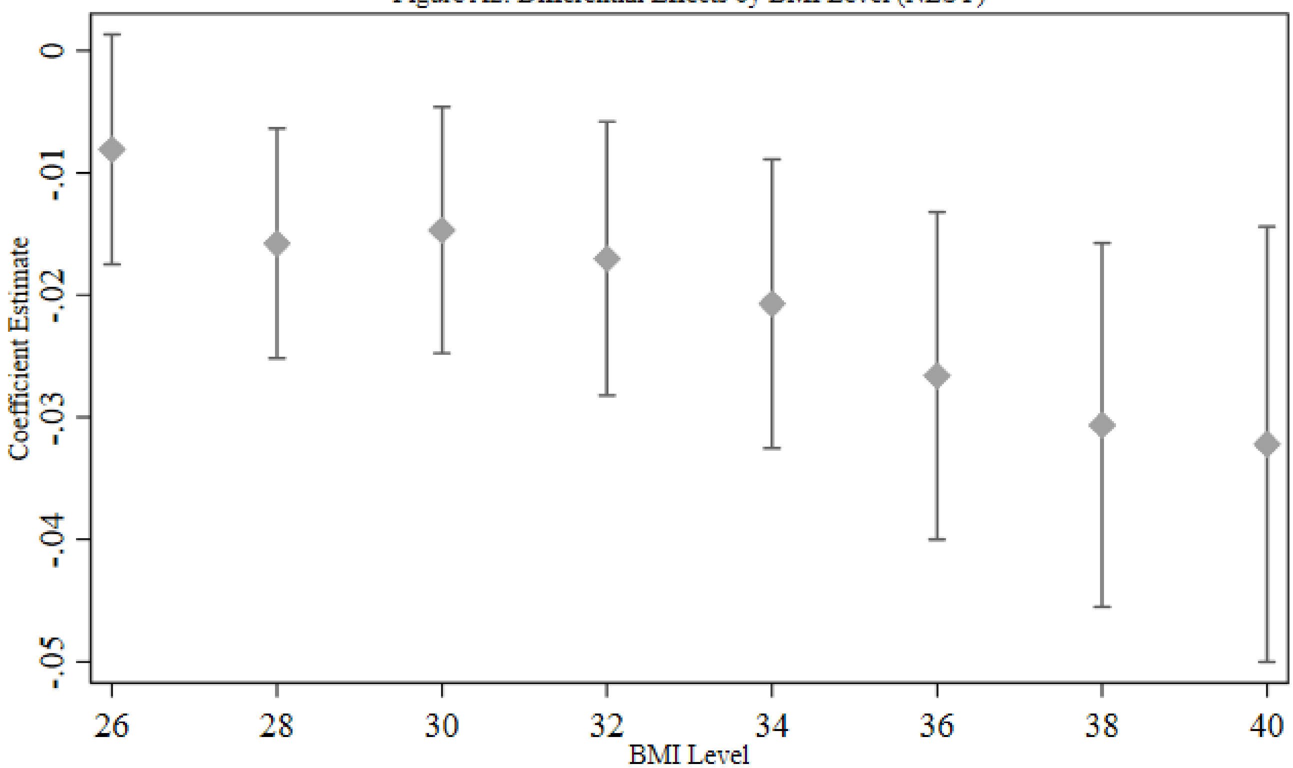
†*Sources: National Longitudinal Surveys, Bureau of Labor Statistics. Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System.* For the NLSY regressions in Panel A, standard errors (in parenthesis) are clustered by county-year. Controls include age and its square, gender, race, highest degree obtained, number of children, marital status, urban residence and ASVAB test scores. Observations are in person-years. For the BRFSS regressions in Panel B, standard errors (in parenthesis) are clustered by state-month. Controls include gender, age and its square, race, education, marital status, and number of children. Observations are in person-months. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Differential Effects by Age Group



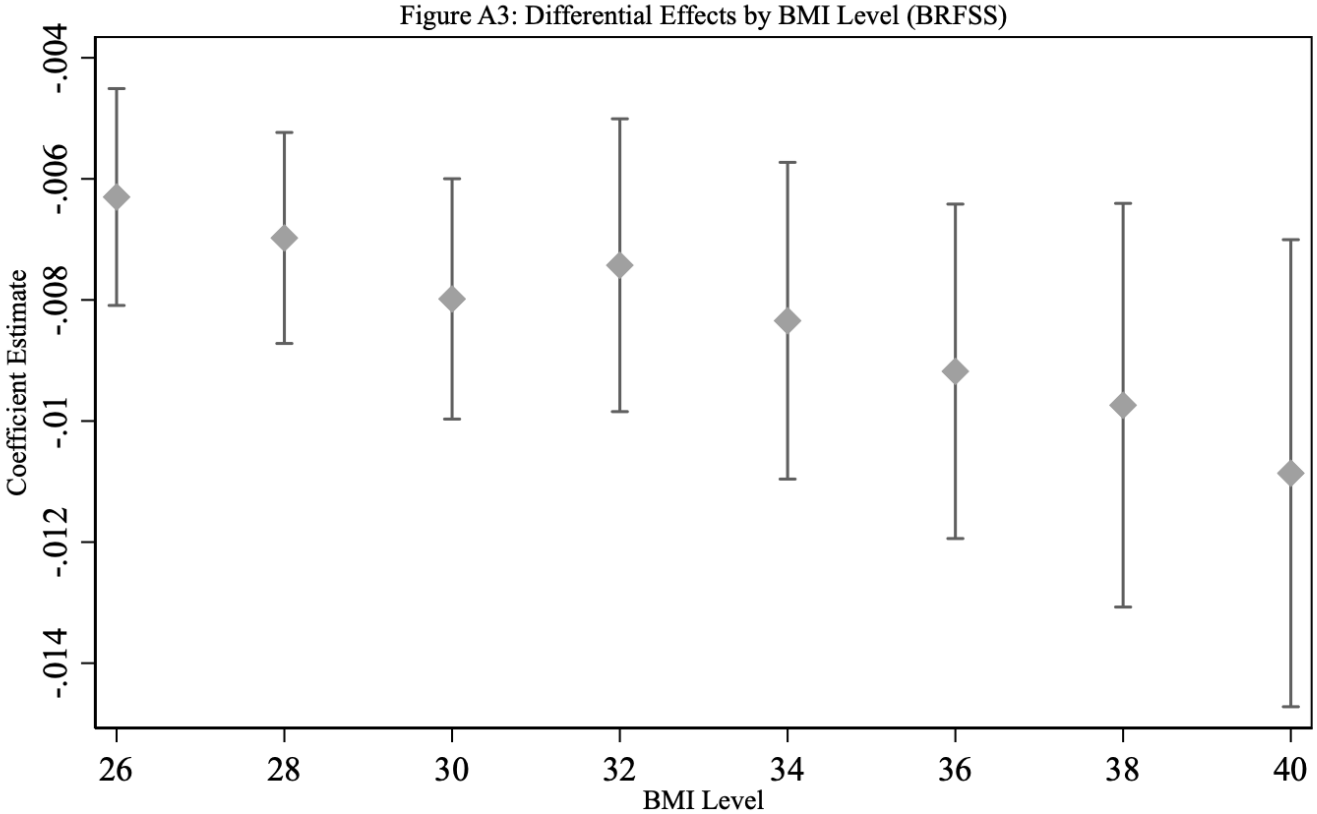
Source: Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System. The y-axis represents the coefficient for the effect of the interaction between obesity and the unemployment rate on the log of income. The x-axis represents the mean age within a 5-year age group. Standard 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.

Figure A2: Differential Effects by BMI Level (NLSY)



Source: National Longitudinal Surveys, Bureau of Labor Statistics. The x-axis represents a BMI cutoff in which the individuals have a BMI greater than or equal to X. The y-axis represents the coefficient for the effect of the interaction between a dummy variable for a given BMI cutoff and the unemployment rate. 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 and year fixed effects.

Figure A3: Differential Effects by BMI Level (BRFSS)



Source: Centers for Disease Control and Prevention (CDC), Behavioral Risk Factor Surveillance System. The x-axis represents a BMI cutoff in which greater than or equal to X. The y-axis represents the coefficient for the effect of the interaction between a dummy variable for a given BMI cutoff and the unemployment rate. Standard errors are clustered by state-month. Controls include age and its square, female, race, number of children, education, and marital status. All estimations include state and month fixed effects.