The Impact of Obesity on Unemployment Duration

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Obesity and its concomitant morbidity have a profound effect on the working careers of Americans. Prior studies document that the obese are less likely to be employed than their nonobese peers. Lower employment may be due to higher job turnover and/or longer duration of unemployment spells. To better understand the connection between obesity and unemployment, we estimate the impact of obesity on the duration of unemployment spells. We estimate a hazard rate model of unemployment duration for individuals of obese and nonobese weights drawn from the National Longitudinal Survey of Youth (1997). Our findings indicate that obese job seekers who are women experience significantly longer spells of unemployment, other things equal. However, the average effects observed for men and women differ for racial and ethnic subgroups with significant effects occurring for nonwhite women and men.

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**1. Introduction**

Millions of American workers are obese. Because this condition affects workers in the prime years of their working lives, it may have a profound effect on their working careers. Recent studies report that obesity causes significantly higher levels of unemployment among

American workers. Appropriate policy design requires that we better understand how these losses occur. To contribute to our understanding of the relationship between obesity and unemployment, we examine the impact of obesity on the duration of unemployment spells.

To the standard job search model found in the labor economics literature we add a variable representing obesity and estimate its differential impact on unemployment duration using a proportional hazard model for data selected from the National Longitudinal Survey of Youth (1979). Our results indicate that obese women have significantly longer spells of unemployment. The mean unemployment spell among obese women is eight days longer on average than that for nonobese women. Thus, the higher unemployment levels observed among obese women is due in part to longer spells of unemployment. In contrast, we find no significant difference due to obesity in the duration of unemployment spells for men.

**2. Prior Studies**

Many studies have examined the relationship between weight and labor earnings in many countries.[[1]](#footnote-1) Although the econometric methods used to handle the potential endogeneity between weight and wages have varied across studies, most (not all) have reported that obese workers, especially women, earn lower wages, other things equal. Averett and Korenman (1996), Cawley (2004), Baum and Ford (2004), and Conley and Glauber (2005) all found a wage penalty for obesity in the range of 0.6–12%. More recently, Han, Norton, and Powell (2011) reported that for women, a one-unit increase in the body mass index (BMI) is directly associated with 1.83% lower hourly wages, while no BMI wage penalty is found for men.[[2]](#footnote-2) However, obesity (BMI>30) is associated with 3.5% lower hourly wages for both women and men. Because Han et al. (2011) included both direct and indirect (via educational attainment and choice of occupation) effects of an increase in BMI, the estimated effect is larger than that found in prior studies. Gilleskie, Han, and Norton (2017)

Fewer studies have examined the employment effects of obesity, but the evidence is drawn from several countries. These studies include field experiments, analyses of the effect of obesity on the probability of employment, and studies of the impact of obesity on the duration of unemployment spells. Rooth (2009) conducted a field experiment in Sweden to discern if employers are less likely to hire obese persons. He finds that job applications sent with the weight-manipulated photos had significantly lower invitations for interviews: Six percentage points lower for men and eight percentage points lower for women.

Caliendo and Lee (2013) found similar results in their study of the employment outcomes of newly unemployed job applicants in Germany. The authors reported that despite making more job applications and engaging more in job training programs, obese women "experienced worse (or at best similar) employment outcomes than normal weight women."

Other studies of the effect of obesity on the probability of unemployment report differing findings: Morris (2007) found that obesity has a significant negative impact on employment for both men and women in a survey of English workers from 1997 and 1998. He finds that failure to account for the endogeneity between obesity and employment led to underestimation of the effect for women. In contrast, Lindeboom, Lundberg, and van der Klaauw (2010), using a long panel sample for Great Britain, reported that obesity decreases employment when estimated in an ordinary least squares regression, but that this effect disappears in an instrumental variable regression model instrumenting obesity with parental obesity and using individual first differences. This suggests that it is unobserved characteristics of the individual rather than obesity that cause employment penalties. Looking beyond Great Britain, Greve (2008) found a negative effect of high BMI on the probability of employment for both men and women in a study using data from a Danish panel survey.

Studies using American data to estimate the impact of obesity on the probability of employment have also reported mixed findings: Norton and Han (2008) used information from specific genes linked to obesity as instrumental variables to estimate the effect of obesity on employment. They found that obesity has no effect on the employment of men or women. Cawley, Han, and Norton (2011) suggested, however, that because genes typically act in concert with other genes, it may be that the genes for neurotransmitters used as instruments may "affect too many things to be valid instruments in most contexts".

Cawley and Danziger (2006) investigated whether obesity is a barrier to employment for former welfare recipients. They found that obese white women are "less likely to work at any survey wave [and] spend a greater percentage of months between waves receiving cash welfare". They commented that "the magnitude of the difference in labor market outcomes between the morbidly obese and those who are less heavy is in some cases similar in magnitude to the differences in these labor market outcomes between high school dropouts and graduates." This suggests that obesity has a strong negative impact for at least some groups in the United States. Renna and Thakur (2010) examined the impact of obesity on employment for another group in the United States population, those nearing retirement. They found that obesity increases the probability of taking an early retirement by 1.5% for men and by 2.5% for women.

Finally, a few studies have considered the relationship between obesity and the duration of unemployment. Härkönen (2007) examined the obesity gap in female unemployment in Finland. After controlling for human capital and demographic characteristics and job search behavior, the author found that obese women have a lower probability of transitioning from unemployment to employment. He attributes this differential to employer discrimination. A similar study using French household data (Paraponaris, Saliba, and Ventelou, 2005) found that "having a BMI greater… than the median BMI decreases the ability to regain employment, and as the deviation increases, the likelihood of employment decreases." The authors also reported that this effect is stronger for women than men. Finally, Katsaiti and Shamsuddin (2016) find a significant impact of obesity on unemployment duration among women in Germany.

While not focused on obesity, Stewart (2001) used a short longitudinal panel to identify the impact of impaired health on the duration of unemployment spells for a sample of unemployed Canadians. She reported that individuals with impaired health experienced significantly longer unemployment spells than unemployed persons without impairments. The longer duration of unemployment among impaired persons led to a larger proportion of the unemployed having impaired health.

Our review of the literature yields mixed findings regarding both the impact of obesity on earnings and on the probability of employment, but many report negative effects. The few studies that examined the connection between poor health or obesity and the duration of unemployment spells consistently found that the negative relationship is driven by longer duration of unemployment between jobs. Unlike the reviewed studies, our research focuses on the impact of obesity on unemployment duration using data for the United States. Further, our use of panel data with repeated unemployment spells (NLSY79, 1992-2006) permits us to control for unobservable individual characteristics that are time-invariant.

**3. Job Search Model of Unemployment Spells**

The number of unemployed workers at any point in time is influenced by both the rate of job turnover and the duration of unemployment spells between jobs which is the factor we focus on. For this research we adopt standard methods used by labor economists studying job search and unemployment.[[3]](#footnote-3) Job search models explicitly formulate the process in which a person invests time, money, and effort in conducting a job search. If a job offer is received, the individual compares the discounted value of future income of accepting the job (**Ve**) to the expected value of future income of continued job search (**Vu**). The individual continues searching until an offer is received for which **Ve > Vu**. The process of searching is combined with the probability of the person receiving an acceptable job offer to generate a prediction of how long the individual will search before he or she will find and accept a job. This period is termed the duration of the unemployment spell. The duration of any given unemployment spell depends upon many factors, including the person’s search efforts, his or her attributes and skills, and the number and type of job openings in the labor market while he or she is searching.

In the classical job search model, the average duration of unemployment (***T***) is expressed as a function of the rate at which a job seeker receives offers (***ρ***) and the probability that he or she will accept an offer that is made (***A***):

(1) ***T = 1 / [ρA]***

The probability of accepting an offer (***A***) depends upon the searcher’s comparison of the expected value of accepting versus the expected value of continued search (**Ve** and **Vu**). The level of labor demand, characteristics of the individual, and the intensity of the individual’s job search determine the magnitude of ***ρ***:

(2) ***ρ = ρ(Ld, Ci, Si)***

Labor demand factors (***Ld***), such as the unemployment rate, determine the number of positions available, other things equal. The characteristics of the job seeker (***Ci***), such as the person’s age, education, and job experience, determine the likelihood of there being a job vacancy that matches the individual, other things equal. Finally, the intensity of the person’s job search (***Si***) influences the time until the job seeker is offered a position because it influences the likelihood of finding a match of his or her characteristics with current vacancies, other things equal.

A tenet of job search theory is that search activities have costs and the higher the cost of search, the lower will be the intensity of the individual’s search activities. Less intense search implies that a longer time is needed to find an appropriate match and, therefore, the longer the duration of the person’s unemployment spell. A large body of empirical research has examined the many factors that influence the intensity of job search. For example, research indicates that more generous unemployment benefits reduce the opportunity cost of unemployment, implying that more generous benefits allow the recipient to be more selective about accepting a position, leading to longer duration of unemployment. In comparison, less generous benefits push searchers into accepting job offers more quickly, other things equal. Alternatively, if the economy is experiencing a recession, research indicates that the lower availability of jobs leads to a longer duration of unemployment, other things equal.[[4]](#footnote-4)

We estimate a reduced form model and are unable to test for specific causes explaining why obesity might lengthen the duration of an unemployment spell. However, there are multiple reasons why the duration of unemployment spells may be longer among obese persons. Some of these stem from the employers’ demand for labor such as employers expecting the average obese worker to incur higher health care costs and thus be reluctant to hire an obese person because of these costs. Alternatively, employers may believe that obese workers are less productive and, again, be reluctant to hire an obese person. Both reasons reduce the rate at which a job seeker receives offers and increase the duration of unemployment. Employers may also engage in taste discrimination where they prefer to hire non-obese workers for reasons not related to productivity or costs thus reducing the probability of the employer making an offer to an obese person. This, again, reduces the rate at which a job seeker receives offers and increasing the duration of unemployment.

To the extent that obesity affects physical mobility and self-esteem, it is also possible that it affects job seekers’ search activities by increasing the cost of job search if the job seeker finds it more difficult to prepare for and/or attend interviews. This will in turn decrease the intensity of search and thereby decrease the rate at which a job seeker interviews and receives offers. This will lengthen the duration of unemployment. The probability that a person will accept an offer of employment depends upon the person's 'reservation wage’, the minimum wage at which an offer would be accepted, and it may be that an obese person expects job tasks associated with a job to be more difficult, this will raise the reservation wage and reduce the probability that he or she will accept an offer, and lengthen the duration of unemployment.

The goal of this research is to establish the existence and magnitude of a net effect of obesity on the average duration of unemployment spells. Accordingly, we estimate the reduced form effect of obesity on the duration of unemployment and do not attempt to distinguish the source of the effect.

**4. Econometric Model**

Our focus is on testing whether obesity has a significantly differential impact on unemployment duration while controlling for unobserved individual-specific effects. The hazard model, shown below, calculates the probability that a spell for individual ***i*** will end given that it has lasted until time ***t***.

**(3)** ***hi(t, zi, β) = h0(t) exp(zi′β)***

In this formulation, ***hi*** denotes individual ***i***’s hazard rate in each period. (Because ***t*** is used to indicate the time at which the unemployment spell ends, to reduce confusion our notation omits a subscript indicating the time for each observation in the panel data.) In this specification, the baseline hazard, denoted by ***h0(t)***,is shared by all and is impacted only by the time variable (that is, how long the spell has lasted up to this point in time). The baseline hazard is multiplied by the term incorporating individual characteristics, measured by the vector ***zi*** and weighted by the vector of estimates ***β***.

Multiple issues arise regarding the specification of the hazard model such as the specific form of the baseline hazard function and the existence of unobserved heterogeneity in the sample. The former concern can be addressed by either ignoring the baseline hazard function, as is the case when estimating the Cox Proportional Hazard (CPH) model or identifying the distribution that best fits the data and estimating a parametric Accelerated Time Failure (AFT) model. In our initial estimates we estimate a Cox Proportional Hazard model; however, after seeing that the variables of interest may violate the proportional assumption, we also estimate the AFT model assuming a Weibull distribution.

The nature of our data which includes repeated unemployment spells for several individuals permits us to control for the latter concern of unobserved heterogeneity by assuming ‘frailty’ in model. Frailty assumes that the baseline hazard function may be similar, but not identical, across certain groups of the population. For example, one might think that the hazard function for some type of spell may be different between men and women or some other group specific factor. In the context of unemployment spells, there may be unobserved heterogeneity across individuals that causes the baseline hazards to be slightly different and if these characteristics are also correlated with our variables of interest, then our estimates may produce biased results. For example, an individual may have low self-esteem that is not reported in the data and this may impact their search for new employment or, more importantly may be correlated with obesity. By assuming frailty across individuals, we allow the unobserved self-esteem to be constant for everyone across his or her multiple unemployment gaps and we allow it to impact different individuals in different way, like individual random effects regression models for panel data.[[5]](#footnote-5)

Frailty is modeled by pre-multiplying the hazard expression by a factor ***θi*** that is specific to individual ***i***. As is standard in the literature, we assumethat ***θi*** is distributed according to the gamma distribution with a normalized mean equal to one, yielding the following equation:

**(4)** ***hi(t, zi, β) = θi h0(t) exp(zi′β)***

The coefficients estimated in the CPH model can be expressed as hazard ratios via the formula assuming a one unit increase in the given parameter of interest multiplied by its estimated coefficient. A hazard ratio less than one (generated by a negative coefficient estimate) indicates that an increase in the variable of interest causes the likelihood that the spell ends in time *t* (given it has lasted to time *t*) to be smaller than the baseline hazard, all else equal. This implies that the unemployment spell has a higher likelihood of continuing (sometimes referred to as increased survivability), i.e., longer duration of the unemployment spell. A hazard ratio larger than one (generated by a positive coefficient estimate) implies that the inclusion of the variable of interest causes the hazard to increase, meaning the likelihood of the unemployment spell ending in time t (given it has lasted to time *t*) has increased over the baseline hazard (sometimes referred to as decreased survivability), i.e., shorter duration of the unemployment spell.

When estimating the AFT model; however, the estimated coefficients, or more specifically , indicates how the survival time of a given individual with a specific value of that covariate is increased (with coefficients greater than zero) or decreased (with coefficients less than zero). These estimates, however, can be easily translated to coefficients similar to that produced by the CPH model and thus hazard ratios using the formula

where is the estimate of the coefficient for the covariate from the CPH model, is the estimate of the coefficient for the covariate from the AFT model, and is the estimated scale parameter of the Weibull distribution.

**5. Data**

The data are drawn from the National Longitudinal Study of Youth, 1997, and span the years from 1997 to 2011. We chose this sample period because it contains the most comprehensive and complete set of variables needed for this model.[[6]](#footnote-6) Unemployment spells (SPELL) are calculated using the weekly employment variable generated by the NLSY indicating if the respondent is employed, unemployed, or out of the labor force during each week within sample period.[[7]](#footnote-7) The length of an unemployment spell is determined by counting the number of consecutive weeks the respondent is classified as unemployed and spells end either by the respondent leaving the workforce or becoming employed. Employer specific measures, discussed below, are matched to unemployment spells using a unique job identifier created by NLSY.[[8]](#footnote-8)

Table 1 provides the names and definitions of the control variables used in the analyses. Because height and weight are not collected consistently across the sample period, we interpolate the missing values. Before interpolation, observations within the reported height and weight that are larger than 2.5 standard deviations of the mean for each individual are assumed to be input errors and are removed. For the height of a respondent, the average height of the remaining observations is used as the height in all periods and the missing weight measures are interpolated using a linear methodology built into the R package *tidyverse*. The imperial measures for each respondent are converted to metric and used to calculate the respondent’s BMI for that year. Using the standard BMI scale, individuals with a BMI between 18.5 and 24.9 are classified as having a normal BMI, individuals with BMI values from 25 to 29.9 were classified as being overweight, and those with BMI values over 30 were classified as being obese.[[9]](#footnote-9)

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1** | | | | | | | | | | | | | |
| **Sample Summary Statistics by BMI Class** | | | | | | | | | | | | | |
|  | |  | **Full Sample** | | **Normal BMI** | | **Overweight BMI** | | **Obese BMI** | | | |
| **Variable** | **Description** | | **Mean** | **St. Dev** | **Mean** | **St. Dev** | **Mean** | **St. Dev** | **Mean** | **St. Dev** | |
| Spell | Length of Unemployment Period in Weeks | | 11.717 | 14.891 | 10.610 | 14.023 | 12.072 | 15.176 | 13.398 | 15.944 | |
| BMI | Body Mass Index | | 27.076 | 6.565 | 22.115 | 1.691 | 27.194 | 1.461 | 36.198 | 5.766 | |
| Normal | =1 if BMI >= 18.5 and BMI < 25 | | 0.473 | 0.499 |  |  |  |  |  |  | |
| Overweight | =1 if BMI >=25 and BMI <30 | | 0.274 | 0.446 |  |  |  |  |  |  | |
| Obese | =1 if BMI >=30 | | 0.254 | 0.435 |  |  |  |  |  |  | |
| Age | Years Old | | 22.751 | 3.549 | 22.000 | 3.390 | 23.129 | 3.512 | 23.742 | 3.573 | |
| Female | =1 if Female | | 0.487 | 0.500 | 0.490 | 0.500 | 0.411 | 0.492 | 0.566 | 0.496 | |
| Child6 | =1 if Child 6 year of age or less present in home | | 0.442 | 0.779 | 0.372 | 0.742 | 0.440 | 0.753 | 0.574 | 0.854 | |
| HH\_Size | Number of individuals with the household | | 3.642 | 1.787 | 3.633 | 1.771 | 3.595 | 1.792 | 3.708 | 1.809 | |
| Gfinc | Total Gross Family Income (IHS) | | 10.475 | 2.452 | 10.554 | 2.353 | 10.450 | 2.551 | 10.353 | 2.515 | |
| Score | Percentile Rank on ASVAB Exam | | 39.152 | 28.691 | 41.669 | 29.462 | 38.428 | 28.456 | 35.240 | 26.962 | |
| Married | =1 if Currently Married | | 0.125 | 0.331 | 0.092 | 0.289 | 0.137 | 0.343 | 0.173 | 0.379 | |
| NeverMarried | =1 if Never Married | | 0.842 | 0.365 | 0.879 | 0.326 | 0.828 | 0.378 | 0.787 | 0.409 | |
| Separated | =1 if Separated, Divorced, or Widowed | | 0.033 | 0.179 | 0.029 | 0.167 | 0.036 | 0.185 | 0.039 | 0.194 | |
| LessHS | =1 if Completed Less than High School | | 0.177 | 0.382 | 0.174 | 0.379 | 0.170 | 0.376 | 0.192 | 0.394 | |
| HS | =1 if Completed High school or GED | | 0.319 | 0.466 | 0.299 | 0.458 | 0.332 | 0.471 | 0.343 | 0.475 | |
| SomeCol | =1 if Completed some college or Associates Degree | | 0.198 | 0.398 | 0.172 | 0.377 | 0.207 | 0.405 | 0.237 | 0.425 | |
| CollegePlus | =1 if Completed Bachelors or Greater | | 0.305 | 0.461 | 0.355 | 0.479 | 0.291 | 0.454 | 0.229 | 0.420 | |
| White | =1 if White | | 0.456 | 0.498 | 0.509 | 0.500 | 0.443 | 0.497 | 0.373 | 0.484 | |
| Black | =1 if Black | | 0.351 | 0.477 | 0.320 | 0.466 | 0.357 | 0.479 | 0.402 | 0.490 | |
| Hispanic | =1 if Hispanic | | 0.193 | 0.394 | 0.171 | 0.377 | 0.200 | 0.400 | 0.224 | 0.417 | |
| Good | =1 if Self-Reported Health as Good | | 0.596 | 0.491 | 0.666 | 0.472 | 0.625 | 0.484 | 0.433 | 0.496 | |
| Average | =1 if Self-Reported Health as Average | | 0.297 | 0.457 | 0.257 | 0.437 | 0.285 | 0.451 | 0.382 | 0.486 | |
| Poor | =1 if Self-Reported Health as Poor | | 0.108 | 0.310 | 0.077 | 0.266 | 0.090 | 0.286 | 0.184 | 0.388 | |
| NorCen | North Central Region (Midwest) | | 0.219 | 0.414 | 0.222 | 0.416 | 0.231 | 0.421 | 0.202 | 0.402 | |
| NorEst | Northeastern Region | | 0.144 | 0.351 | 0.153 | 0.360 | 0.137 | 0.344 | 0.133 | 0.340 | |
| South | South Region | | 0.423 | 0.494 | 0.404 | 0.491 | 0.415 | 0.493 | 0.467 | 0.499 | |
| West | West Region | | 0.214 | 0.410 | 0.221 | 0.415 | 0.217 | 0.412 | 0.197 | 0.398 | |
| SearchCT | Number of Methods Used for Job Search During Gap (1 - 12) | | 3.125 | 1.900 | 3.013 | 1.818 | 3.181 | 1.921 | 3.274 | 2.009 | |
| Ten | Weeks worked in current Job | | 23.784 | 54.429 | 21.689 | 50.945 | 25.195 | 57.417 | 26.165 | 57.196 | |
| Exp | Cumulative total of weeks employed at time of unemployment spell | | 191.856 | 152.048 | 169.662 | 142.130 | 203.462 | 154.780 | 220.698 | 160.528 | |
| Union | =1 if Job before gap had was union | | 0.019 | 0.137 | 0.015 | 0.123 | 0.023 | 0.148 | 0.022 | 0.147 | |
| Quit | =1 if Job ended voluntary | | 0.027 | 0.161 | 0.027 | 0.161 | 0.027 | 0.162 | 0.026 | 0.160 | |
| Forced | =1 if Job ended by being fired | | 0.007 | 0.084 | 0.006 | 0.080 | 0.007 | 0.086 | 0.008 | 0.091 | |
| Ended | =1 if Job ended due to firm circumstances | | 0.025 | 0.157 | 0.025 | 0.156 | 0.027 | 0.162 | 0.024 | 0.153 | |
| Illness | =1 if Job ended due to illness | | 0.001 | 0.030 | 0.001 | 0.023 | 0.001 | 0.034 | 0.001 | 0.038 | |
| Unknown | =1 if Job ending cause unknown | | 0.940 | 0.238 | 0.941 | 0.235 | 0.938 | 0.242 | 0.940 | 0.238 | |
| URate | Regional Unemployment Rate | | 6.004 | 1.861 | 5.731 | 1.678 | 6.118 | 1.893 | 6.391 | 2.058 | |
| Observations | Individual-Spell Count | | 16,210 | | 7,662 | | 4,438 | | 4,110 | |

It is possible that BMI and unemployment may be endogenous via two possible channels. The first is that concurrent unemployment may increase the probability of obesity and the second is that unemployment and obesity may be correlated to unobserved individual characteristics such as self-esteem or depression. In the former case, we estimate the models using both current and lagged BMI and show the results are consistent for either measure. For the latter case, we estimate the models assuming frailty across the individual.

Other independent variables included in the analyses are of two types: the first describes the *personal characteristics* of the individual who experiences the unemployment spell, and we link the annual reported values of the individual characteristics to the year in which the unemployment spell started. Besides obesity, we include age (Age), sex (Female), the presence of a child six years of age or young within the household (Child6), the household size (HH\_Size), a measure of gross family income (Gfinc),[[10]](#footnote-10) marital status (Married, NeverMarried\*, Separated), education (LessHS, HS\*, SomeCol, and CollegePlus), self-reported health status (Good\*, Average, Poor), and Census Region of residency (NorCen, NorEst\*, South, West).[[11]](#footnote-11) To capture the job search behavior for a respondent during each employment spell, we create the variable (SERACHCT) which is a count of the number of search methods reported to have been utilized by the respondent during each unemployment spell.[[12]](#footnote-12) The time invariant measures are the respondent’s race (White\*, Black, and Hispanic) and ability (Score) as measured by the ASVAB Math and Verbal Score Percentile which is calculated by the NLSY and is similar to the Armed Forces Qualification Test (AFQT) utilized in the other surveys.

The second type of independent variables are *job-specific characteristics* including the respondent’s tenure (Ten) in the job immediately prior to the unemployment spell, total labor market experience (Exp) measured as the sum of all previous employment tenures, the occupation (OCC) and industry (IND) of the job immediately prior to the unemployment spell[[13]](#footnote-13) and whether that job included union representation (Union). We also include indicator variables for reason that the unemployment spell started (Quit, Forced, Ended, Illness, Unknown\*).[[14]](#footnote-14) Finally, to capture market conditions we include the unemployment rate (Urate) for the Census region individual is reported to live in obtained from the Saint Louis Federal Reserve Bank’s FRED website and the monthly rates are matched with the month and year the unemployment spell begins.

**6. Results**

**6.1 Descriptive Analysis**

For the full sample of 16,210 unemployment spells, Table 1 shows the average unemployment spell lasted 11.7 weeks. There are 7,662 spells for respondents with a BMI in the normal range with an average unemployment spell of 10.6 weeks, 4,438 spells by those within the overweight BMI class with an average unemployment spell of about 12.1 weeks, and the remaining 4,110 spells involve those classified as obese and experience unemployment spells lasting an average of 13.4 weeks. The increase in the spell duration across BMI classification is statistically significant at the highest level between each BMI class.

Chart

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Figure 1 shows the Kaplan–Meier (K-M) estimated survival curves for the full sample for each of the three BMI categories defined. Survival probability in this case is the likelihood that an unemployment spell will continue given that it has lasted until that time. The median survival time is the point at which the survival probability is 50% and is shown with the dashed lines and occurs at 5 weeks for those in the normal BMI class, 6 weeks for those in the overweight class, and 8 weeks for those in the obese class. We also see that the survival curves are shifted out beyond the 95% confidence intervals for those in each class over most of the time in weeks.[[15]](#footnote-15)

While these factors seem to support the hypothesis that unemployment spell is impacted by BMI classification, looking at the other variables in columns two, three, and four of Table 1 show that the characteristics of the respondents also vary by BMI class. As BMI class increases respondents tend to be older, more likely to have a child under the age of six present in the household, tend to have a smaller gross family income, a lower score on the cognitive test, and more likely to be married. The mean percentage of respondents with less than high school, high school, and some college increases with the BMI category while the percentage that have more than four years of college decreases with the BMI category. The percentage of respondents that are White declines as one moves up the BMI classifications and while the share of Black and Hispanic rises. Those in the obese categories employed more search methods than the other two categories, had a longer tenure in their previous job, and have a longer period of overall employment.

Chart

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Figures 2 and 3 show the K-M survival curves for males and female subsamples respectively and the impact of BMI class appears to still hold. For both males and females, the mean duration, or point where survival of a spell is at 50%, are the same at 5, 6 and 8 weeks for normal, overweight, and obese classes. Figure 4, 5, and 6 break the sample into racial subsamples and the same results hold with the unusual the obesity impact being strongest for Hispanics and smallest between the obese and overweight respondents for Whites.

Chart

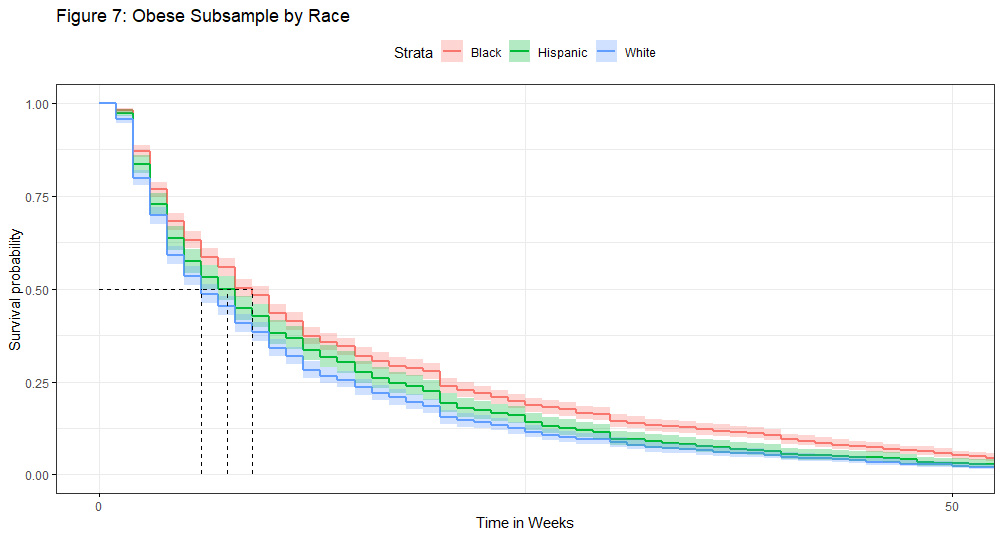
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Of particular interest are Figures 7 and 8 which show the K-M survival curves for only those within the obese subsample divided by race and sex. In Figure 7 we see that among obese individuals, Blacks have the largest likelihood that an unemployment spell will continue with a mean of 9 weeks, followed by Hispanics with a mean of 7.5 weeks and Whites with a mean of 6 weeks. Figure 8 shows the obese subsample split by sex and it appears that both obese men and women suffer similar impacts on their duration, both with means of 8 weeks. Looking at the summary statistics for each of the BMI classification subsamples shown in later three columns of Table 1 indicate there are other differences that must be accounted for.

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**6.2 Regression Analysis**

Table 2 reports the coefficient estimates from several specifications of the simplest version of the model where unemployment spell length is regressed on indicators denoting belong to the overweight and obese BMI classes. The first three columns show the results from the Cox Proportional Hazard model where a coefficient estimate less than zero indicates the hazard rate, or likelihood of ending a spell, is decreasing. We see that individuals that are obese at the start of the spell (column one) or in the year prior to the start of the spell (column two) see a statistically significant extension of their unemployment spell compared to those of normal BMI as indicated by a hazard ratio of about 0.81. The same is true, but to a lesser extent, for those individuals with a BMI within the overweight range with a hazard ratio of about 0.89. The magnitudes between the current and lagged BMI are the very similar across the two models indicating that simultaneity of the BMI classification and an unemployment spell is not biasing the results, however, the model using lagged BMI classification does have a slightly better fit to the data.

A second concern regarding the endogeneity of the BMI classification and unemployment spell is that they may both be correlated to an unobserved individual characteristic. We address this by assuming individual frailty within the model which allows the base hazard to differ by individual. The results, shown in column three, see an increase in the magnitude of the effect while retaining the statistical significance. Specifically, for overweight individual the hazard ratio falls to 0.86 and for obese individuals the hazard rate falls to 0.76.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Duration Models with only BMI Classifications** | | | | | | | | |
| Coefficient Estimates for the Cox Proportional Hazard and AFT Models | | | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| (Intercept) |  |  |  | 2.34\*\*\* | 2.34\*\*\* | 2.25\*\*\* | 2.25\*\*\* |
|  |  |  |  | (0.01) | (0.01) | (0.02) | (0.02) |
| Overweight | -0.12\*\*\* | -0.13\*\*\* | -0.15\*\*\* | 0.13\*\*\* | 0.15\*\*\* | 0.16\*\*\* | 0.20\*\*\* |
|  | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | -0.02 |
| Obese | -0.21\*\*\* | -0.21\*\*\* | -0.28\*\*\* | 0.24\*\*\* | 0.23\*\*\* | 0.35\*\*\* | 0.34\*\*\* |
|  | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | -0.03 |
| Log(scale) |  |  |  | 0.05\*\*\* | 0.04\*\*\* | -0.30\*\*\* | -0.30\*\*\* |
|  |  |  |  | (0.01) | (0.01) | (0.01) | -0.01 |
| AIC | 281732.03 | 277348.91 | 280772.14 | 111991.77 | 110438.61 | 108858.19 | 107366 |
| Num. obs. | 16210 | 15984 | 16210 | 16210 | 15984 | 16210 | 15984 |
| BIC |  |  |  | 112022.55 | 110469.32 | 134361.91 | 132583.39 |
| Log Likelihood |  |  |  | -55991.89 | -55215.30 | -51114.08 | -50399.42 |
| \*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05. For columns 1, 2, and 3, hazard ratios are obtained via exp(coefficient). For columns 4, 5, 6, and 7, hazard ratios are obtained via exp(-coefficient \* 1/exp (Log(scale))). | | | | | | | | |

A third concern is that the model may be mis-specified. Specifically, the Cox Proportional Hazard model assumes that coefficients impact the baseline hazard proportionally meaning that the survival curves are parallel. This assumption of proportionality can be tested using a Schoenfeld residual test and the result of such a test using the results from columns 1, 2, or 3, rejects the null hypothesis of proportional hazards for the obese coefficient.[[16]](#footnote-16) The solution is to estimate a parametric version of the model known as an Accelerated Failure Time (AFT) model. Based on a visual inspection of the survival curves (see Figure 1), we assume a Weibull distribution and estimate the model with current BMI classification (column four), lagged BMI (column five), lagged BMI with individual frailty (column six) and lagged BMI with individual frailty (column seven).[[17]](#footnote-17) In all estimates, the coefficients are statistically significant at the highest level and clearly show that unemployment duration lasts longer for individual with an overweight BMI and longer still for individuals with an obese BMI classification indicating that BMI may be having an impact on unemployment durations.[[18]](#footnote-18) Furthermore, the hazard ratio for overweight individuals in column seven is about 0.76 and for obese the hazard ratio is about 0.63.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 3: AFT Model with Additional Covariates** | | | | | | |
| Duration of Unemployment Spells – Weibull Distribution | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| (Intercept) | 1.5820\*\*\* | 1.4655\*\*\* | 1.6167\*\*\* | 1.5126\*\*\* | 1.7502\*\*\* | 1.6504\*\*\* |
|  | (0.0924) | (0.0933) | (0.0924) | (0.0936) | (0.2278) | (0.2272) |
| Overweight | 0.0368 | 0.0611\*\* | 0.0340 | 0.0557\*\* | 0.0354 | 0.0498\* |
|  | (0.0208) | (0.0206) | (0.0206) | (0.0204) | (0.0204) | (0.0202) |
| Obese | 0.1319\*\*\* | 0.1190\*\*\* | 0.1195\*\*\* | 0.1000\*\*\* | 0.1142\*\*\* | 0.0932\*\*\* |
|  | (0.0254) | (0.0254) | (0.0250) | (0.0250) | (0.0248) | (0.0248) |
| Female | -0.0985\*\*\* | -0.0916\*\*\* | -0.0829\*\*\* | -0.0779\*\*\* | -0.0874\*\*\* | -0.0819\*\*\* |
|  | (0.0237) | (0.0238) | (0.0233) | (0.0234) | (0.0235) | (0.0236) |
| Age | 0.0501\*\*\* | 0.0549\*\*\* | 0.0247\*\*\* | 0.0305\*\*\* | 0.0271\*\*\* | 0.0335\*\*\* |
|  | (0.0040) | (0.0040) | (0.0043) | (0.0044) | (0.0043) | (0.0044) |
| Married | -0.0486 | -0.0509 | -0.0405 | -0.0424 | -0.0388 | -0.0416 |
|  | (0.0281) | (0.0281) | (0.0278) | (0.0278) | (0.0276) | (0.0276) |
| Separated | 0.1058\* | 0.0886 | 0.0734 | 0.0589 | 0.0644 | 0.0471 |
|  | (0.0499) | (0.0498) | (0.0493) | (0.0492) | (0.0492) | (0.0490) |
| Black | 0.2278\*\*\* | 0.2255\*\*\* | 0.2053\*\*\* | 0.2026\*\*\* | 0.2005\*\*\* | 0.1983\*\*\* |
|  | (0.0310) | (0.0311) | (0.0304) | (0.0305) | (0.0302) | (0.0303) |
| Hispanic | 0.0126 | 0.0115 | 0.0155 | 0.0146 | 0.0137 | 0.0132 |
|  | (0.0330) | (0.0330) | (0.0323) | (0.0324) | (0.0321) | (0.0321) |
| Child6 | 0.0001 | 0.0019 | 0.0053 | 0.0076 | 0.0070 | 0.0095 |
|  | (0.0117) | (0.0117) | (0.0116) | (0.0116) | (0.0115) | (0.0115) |
| GFinc | -0.0104\*\* | -0.0114\*\*\* | -0.0109\*\*\* | -0.0118\*\*\* | -0.0121\*\*\* | -0.0132\*\*\* |
|  | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) |
| HS | -0.0841\*\* | -0.0687\* | -0.0849\*\* | -0.0704\* | -0.0870\*\* | -0.0729\* |
|  | (0.0297) | (0.0298) | (0.0293) | (0.0294) | (0.0290) | (0.0292) |
| SomeCol | -0.1208\*\*\* | -0.1348\*\*\* | -0.1300\*\*\* | -0.1412\*\*\* | -0.1322\*\*\* | -0.1443\*\*\* |
|  | (0.0349) | (0.0351) | (0.0344) | (0.0346) | (0.0342) | (0.0344) |
| CollegePlus | -0.0980\*\* | -0.1335\*\*\* | -0.1172\*\*\* | -0.1467\*\*\* | -0.1091\*\*\* | -0.1413\*\*\* |
|  | (0.0321) | (0.0328) | (0.0318) | (0.0324) | (0.0316) | (0.0321) |
| Score | -0.0055\*\*\* | -0.0051\*\*\* | -0.0054\*\*\* | -0.0050\*\*\* | -0.0054\*\*\* | -0.0050\*\*\* |
|  | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Ten | 0.0010\*\*\* | 0.0010\*\*\* | 0.0010\*\*\* | 0.0010\*\*\* | -0.0004\* | -0.0005\* |
|  | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Exp | 0.0003\*\* | 0.0003\*\* | 0.0001 | 0.0001 | 0.0000 | -0.0000 |
|  | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Average | -0.0039 | -0.0019 | -0.0101 | -0.0078 | -0.0104 | -0.0078 |
|  | (0.0180) | (0.0181) | (0.0178) | (0.0179) | (0.0177) | (0.0178) |
| Poor | -0.0432 | -0.0404 | -0.0525 | -0.0499 | -0.0566\* | -0.0545\* |
|  | (0.0276) | (0.0276) | (0.0272) | (0.0273) | (0.0271) | (0.0271) |
| NorCen | -0.0817\* | -0.0837\* | -0.1154\*\* | -0.1190\*\* | -0.1130\*\* | -0.1168\*\* |
|  | (0.0367) | (0.0368) | (0.0360) | (0.0362) | (0.0357) | (0.0359) |
| South | -0.1002\*\* | -0.0978\*\* | -0.1197\*\*\* | -0.1184\*\*\* | -0.1180\*\*\* | -0.1166\*\*\* |
|  | (0.0332) | (0.0333) | (0.0326) | (0.0328) | (0.0324) | (0.0325) |
| **Table 3: AFT Model with Additional Covariates (cont)** | | | | | | |
| Duration of Unemployment Spells – Weibull Distribution | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| West | -0.1280\*\*\* | -0.1258\*\*\* | -0.1972\*\*\* | -0.1929\*\*\* | -0.1998\*\*\* | -0.1950\*\*\* |
|  | (0.0371) | (0.0373) | (0.0368) | (0.0370) | (0.0365) | (0.0367) |
| URATE |  |  | 0.0736\*\*\* | 0.0691\*\*\* | 0.0753\*\*\* | 0.0706\*\*\* |
|  |  |  | (0.0054) | (0.0055) | (0.0054) | (0.0054) |
| UNION |  |  | 0.0490 | 0.0131 | -0.0087 | -0.0496 |
|  |  |  | (0.0534) | (0.0534) | (0.0546) | (0.0548) |
| SearchCT |  |  | 0.0472\*\*\* | 0.0458\*\*\* | 0.0446\*\*\* | 0.0432\*\*\* |
|  |  |  | (0.0040) | (0.0040) | (0.0040) | (0.0040) |
| Forced |  |  | 0.4636\*\*\* | 0.4478\*\*\* | 0.2467\*\* | 0.2278\*\* |
|  |  |  | (0.0809) | (0.0807) | (0.0825) | (0.0823) |
| Ended |  |  | 0.4108\*\*\* | 0.4177\*\*\* | 0.2042\*\*\* | 0.2048\*\*\* |
|  |  |  | (0.0444) | (0.0444) | (0.0474) | (0.0474) |
| Illness |  |  | 0.1187 | 0.1448 | -0.1435 | -0.1287 |
|  |  |  | (0.2125) | (0.2150) | (0.2109) | (0.2128) |
| Quit |  |  | 0.3093\*\*\* | 0.3086\*\*\* | 0.0936\* | 0.0916\* |
|  |  |  | (0.0436) | (0.0436) | (0.0461) | (0.0461) |
| Occupation Fixed Effects | No | No | No | No | Yes | Yes |
| Industry Fixed Effects | No | No | No | No | Yes | Yes |
| Log(scale) | -0.3186\*\*\* | -0.3242\*\*\* | -0.3270\*\*\* | -0.3318\*\*\* | -0.3336\*\*\* | -0.3385\*\*\* |
|  | (0.0067) | (0.0067) | (0.0067) | (0.0067) | (0.0067) | (0.0067) |
| AIC | 107987.4825 | 106455.7981 | 107644.9211 | 106140.5574 | 107505.6264 | 105994.7576 |
| BIC | 132741.4565 | 130948.0442 | 132135.5496 | 130375.5881 | 132088.7167 | 130300.9573 |
| Log Likelihood | -50776.1747 | -50038.5319 | -50639.1241 | -49914.4060 | -50557.4584 | -49832.2385 |
| Num. obs. | 16210 | 15984 | 16210 | 15984 | 16210 | 15984 |
| \*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05. For columns 1, 2, and 3, hazard ratios are obtained via exp(coefficient). For columns 4, 5, 6, and 7, hazard ratios are obtained via exp(-coefficient \* 1/exp (Log(scale))). | | | | | | |

Table 3 shows the results from the accelerated failure model assuming a Weibull baseline hazard function with individual frailty when additional covariates are added to the model. Columns (1) and (2) show the results when adding the set of individual specific covariates, columns (3) and (4) add job specific covariates without controlling for occupation or industry while columns (5) and (6) include fixed effects for both occupation and industry. Among the six columns in Table 3, columns (1), (3), and (5) use the current BMI classification while columns (2), (4), and (6) use the lagged BMI classification. In all cases the unemployment spell of individuals with a BMI classification of obsess lasts 1.14 to 1.10 times longer that of a normal weight individual. This 10 to 14% increase implies that an obese individual will experience an unemployment spell lasting about 1.6 weeks longer than those with normal BMI, all else equal. For those that are overweight, the magnitude of the impact of the BMI classification is more sensitive to the specification with the impact ranging between 5 and 6% or between 5 to 7 days. In terms of statistical significance, the impact is only significant when the lagged BMI classification is used and then only significant at the 1% level at best.

Across all specifications in Table 3, the impact from other covariates are rather stable in both magnitude and statistical significance across models with some larger changes being observed for the job-specific measure when the occupations and industry are controlled for. Among those that are significant we observe that women see a shorter duration compared to men, on average, while age increases the duration of unemployment spells. As we have seen already, unemployment spells for Black individuals tend to be significantly longer compared to Whites while Hispanic see no statistically significant change in duration. Having a higher gross family income and increasing levels of education and higher cognitive skills all shorten the duration of an unemployment spell as one would expect.

The only case where signs change across specifications is when the tenure variable is used. Having a longer tenure at a specific job tends to slightly increase the duration of the subsequent unemployment spell except when we control for occupation and industry after which the impact becomes negative indicating a shorter duration. The size of the impact, however, is very small making it economically insignificant. Similarly, the impact from self-reported poor health becomes statistically significant when we control for occupation and industry, however, the sign is not as expected as poor health is shortening the unemployment spell. It is important to keep in mind that in our sample, an individual that leaves a job and takes time off (that is, not looking for work) due to an illness, they are not included in our sample until they start looking for work again. Additionally there may be some effect from health insurance typically being tied to employment. Region also seems to impact the length of employment with those in the reference category of the Northeast having the longest duration while those in the West have the shortest duration. Given the economic expansion in many western states, this is not a surprising result.

Focusing on the last two columns of Table 3 we see that higher unemployment rates within the region extends the duration, as expected, as does the case where a person if fired, quit, or the job ended compared to those cases where job ending is unknown. We see a similar impact, albeit not statistically significant, when an unemployment spell is started due to illness as we did with poor self-reported health. Two other interesting results are that union representation does impact the duration of the subsequent unemployment spell and the more search methods an individual uses, the longer the duration. This result, however, could be endogenous as an individual utilizes more search options the longer an unemployment spell lasts. We are not concerned with this possible endogeneity as it is not related to the variables in question.

**6.3 Analysis by Types**

As in the K-M survival graphs above, we investigate how the BMI impact on unemployment duration may vary by sex and race. Table 4 shows the results when we split the sex identifier and the race identifier variable into the three BMI classifications (using the lagged BMI from this point forward) and estimate the full model with occupation and industry controls.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 4: BMI Classification Interactions** | | | | | |
| Duration of Unemployment Spells – Weibull Baseline Hazard | | | | | |
|  | Female | Male | White | Black | Hispanic |
| Normal BMI | -0.0965\*\*\* | REF | REF | 0.2157\*\*\* | -0.0319 |
|  | (0.0289) | (0.0360) | (0.0406) |
| Overweight BMI | -0.0127 | 0.0226 | 0.0602\* | 0.2245\*\*\* | 0.0703 |
|  | (0.0337) | (0.0273) | (0.0300) | (0.0389) | (0.0443) |
| Obese BMI | 0.0147 | 0.0761\* | 0.0794\* | 0.2817\*\*\* | 0.1315\*\* |
|  | (0.0357) | (0.0354) | (0.0373) | (0.0416) | (0.0491) |
| Log(scale) | -0.3386\*\*\* | | -0.3386\*\*\* | | |
|  | (0.0067) | | (0.0067) | | |
| (Intercept) | 1.6604\*\*\* | | 1.6561\*\*\* | | |
|  | (0.2275) | | (0.2276) | | |
| AIC | 105995.7023 | | 105993.2659 | | |
| BIC | 130306.4228 | | 130295.7121 | | |
| Log Likelihood | -49832.1221 | | -49831.9814 | | |
| Num. obs. | 15984 | | 15984 | | |
| \*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05 | | | | | |

The first two columns of results in Table 4 show the model where the female identifier is replaced with the sex identifiers split across BMI classification and we see clear indications that the sexes are treated differently. Specific we see that women of normal BMI see unemployment spells about 9% shorter than men with a normal BMI while women of overweight or obese BMI see statistically similar durations as men of normal BMI. The only group in these results to see an increase in their unemployment spells are obese men enduring a 7% longer unemployment spell on average.

The last three columns in Table 4 create similar variables as in the first two columns with the races being divided out by BMI class. Whites with a BMI that is classified as overweight or obese see an increase in the duration of their unemployment spell of about 7 to 8% while only obese Hispanics see an increase duration of about 13%. Blacks of any BMI classifications see very large increases in duration compared to Whites with a normal BMI. normal and overweight Black individuals see about a 20%, or almost two weeks, increase in unemployment spells while Blacks classified as obese see an almost 30% increase in unemployment spell duration. In terms of hazard ratios, normal and overweight Blacks have a hazard ratio of about 0.74 and obese Blacks see a hazard ratio of about 0.67 compared to Whites with a normal BMI.

Table 5 breaks the race results down further by splitting each race into the two sexes. We see that when broken down by sex, the BMI of White men has no discernible impact on the duration of their unemployment and many of the White result in Table 4 are being driving by the still present and highly significant shorter duration enjoyed by White women with a normal BMI. In the case of Hispanics, both men and women with a normal BMI and women classified as overweight seem to enjoy shorter durations while obese men see longer unemployment spells. Unfortunately, these results are statistically significant likely driven by the relatively low observation counts within each of these smaller categories.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 5: BMI Classification Interactions with Sex and Race** | | | | | | |
| Duration of Unemployment Spells – Weibull Baseline Hazard | | | | | | |
|  | White | | Black | | Hispanic | |
|  | Male | Female | Male | Female | Male | Female |
| Normal BMI | REF | -0.1365\*\*\* | 0.2008\*\*\* | 0.1094\* | -0.1058 | -0.0896 |
|  | (0.0390) | (0.0480) | (0.0486) | (0.0569) | (0.0548) |
| Overweight BMI | 0.0257 | -0.0271 | 0.1307\* | 0.1917\*\*\* | 0.0728 | -0.0677 |
|  | (0.0388) | (0.0503) | (0.0520) | (0.0523) | (0.0580) | (0.0650) |
| Obese BMI | 0.0244 | 0.0039 | 0.2551\*\*\* | 0.1867\*\*\* | 0.1200 | 0.0144 |
|  | (0.0524) | (0.0540) | (0.0609) | (0.0527) | (0.0665) | (0.0690) |
| Log(scale) | -0.3389\*\*\*  -0.3389\*\*\*  -0.3386\*\*\*  (0.0067) | | | | | |
|  | (0.0067)  (0.0067) | | | | | |
| (Intercept) | 1.6857\*\*\*  1.6857\*\*\*  1.6561\*\*\*  (0.2276) | | | | | |
|  | (0.2283)  (0.2283) | | | | | |
| AIC | 105986.6148  105986.6148 | | | | | |
| BIC | 130289.6967  130289.6967 | | | | | |
| Log Likelihood | -49828.5731  -49828.5731 | | | | | |
| Num. obs. | 15984  15984 | | | | | |
| \*\*\*p < 0.001; \*\*p < 0.01; \*p < 0.05 | | | | | |  |

The largest effects are again seen by Black respondents shown in the middle two columns of Table 5. Specifically, Black males with a normal BMI have a 20% increase in their unemployment spell while Black men classified as overweight see only a 13% increase in duration. Obese black men see an even larger impact at more than 25% (with a corresponding hazard ratio of about 0.70). Interesting, Black women within the normal category fare better than their male counterparts; however, they still experience longer unemployment spells compared to White men. Black women within the overweight and obese categories also endure unemployment spells about 20% longer than White men (with a hazard ratio of about 0.76).

**7. Discussion**

Prior studies find that obesity causes significantly higher unemployment among American workers. Others have suggested that it is unobserved characteristics of the individual rather than obesity that cause these employment penalties (e.g., Lindeboom et al., 2010). Using data from the National Longitudinal Study of Youth (1990), we estimate the duration of unemployment spells assuming individual frailty (thus controlling for individual unobserved effects) and find that individuals classified as overweight endure unemployment spells that are about 6% longer than those with normal BMI and those classified as obese spend about 10% more time unemployed, all else equal. In terms of weeks, this equates to about one week for those overweight and about 1.5 weeks for those that are obese.

We further brake down the impact of BMI by race and gender we find that White women of normal BMI see shorter unemployment spells compared to White men of normal BMI of almost 14% and that the no other White individual suffers different unemployment spells compared to White men of normal BMI. Conversely, all Black individuals see significantly longer unemployment spells with normal and obese Black mean seeing the longest durations, similar to overweigh and obese Black women, while normal weight Black women and overweight Black men see the shortest extension of unemployment spells compared to White men with normal BMI. While not statistically significant, Hispanic men and women of normal BMI and overweight Hispanic women see shorter unemployment durations and obese Hispanic men see longer durations compared to White men of normal BMI. These results are generally stable across several specifications of the model including measure of both individual and job specific covariates.

In short, our results indicate that BMI can have an impact on the duration of an unemployment spell and that for most, Blacks especially, this impact is negative. For some, however, being at a normal BMI may speed up the process of obtain a new job, at least for White and Hispanics. Because so many millions of workers are obese or at risk of obesity, the potential costs of this problem are of great policy importance. However, appropriate policy design requires that we have a detailed understanding of the nature of the impact of obesity in the labor market and factors that do and do not appear to play a role. The findings reported here add to our understanding of how obesity impacts the duration of unemployment spells for men and women and how the effect varies across racial and ethnic groups.

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1. Averett and Korenman (1996), Baum & Ford (2004), Behrman and Rosenzweig (2001), Bhattacharya and Bundorf (2005), Cawley (2000, 2004), Cawley, Grabka, and Lillard (2005), Cawley and Danziger (2006), Conley and Glauber (2006), Garcia and Quintana-Domeque (2006), Gregory and Ruhm (2006), Han, Norton, and Stearns (2009), Han, Norton, and Powell (2011), Morris (2007), Norton and Han (2008), Pagan and Davila (1997), and Sabia and Rees (2012). [↑](#footnote-ref-1)
2. Body mass index is defined as the individual's body mass divided by the square of his or her height. [↑](#footnote-ref-2)
3. See Eckstein and van den Berg (2007) for a brief review of the theoretical job search model. [↑](#footnote-ref-3)
4. See Devine and Kiefer (1991) for a survey of the early literature and Eckstein and van den Berg (2007) for a more recent survey of the empirical literature. [↑](#footnote-ref-4)
5. See Gutierrez (2002) for details about parametric frailty survival models. [↑](#footnote-ref-5)
6. A previous version of this paper attempted to use data NLSY 1979 cohort; however, there were not sufficient observations within the obese category to produce stable results. [↑](#footnote-ref-6)
7. An alternative approach to identify unemployment spells is to use the questions which ask about the start and stop of employment. One problem with this method is that the question instructs the interviewer to insert the interview date if the respondent is still employed causing confusion in the coding. Additionally, using these questions make measuring spells across calendar years difficult and there is no indication if the respondent is unemployed or out of the labor force. [↑](#footnote-ref-7)
8. In the weekly data, unemployment spells that are ended by employment are indicated using a unique job id. [↑](#footnote-ref-8)
9. Centers for Disease Control and Prevention (2017). We remove individuals with a BMI classified as underweight and we can show the estimates to be robust to the removal of individuals classified as underweight since such a low BMI may be an indication of an unobserved illness. [↑](#footnote-ref-9)
10. The reported gross family income is adjusted using the Inverse Hyperbolic Sine method which is like the natural log yet allows observations equal to zero. [↑](#footnote-ref-10)
11. The reference category is indicated with an asterisk. For the race category, individuals classified as “mixed” are removed. [↑](#footnote-ref-11)
12. Many unemployment spells list no job search activities which we suspect is an error in the data collection rather than a lack of job search activity. [↑](#footnote-ref-12)
13. For both the occupation and industry we aggregate the individual codes into the two-digit codes defined by the census. [↑](#footnote-ref-13)
14. There are several missing or skipped observations for this question, so the category UNKNOWN is used to capture these events. [↑](#footnote-ref-14)
15. We limit the graphs to the first 50 weeks as the curves are essentially overlapping after that point. The fact that the curves overlap and in some cases cross is another case of the violation of the proportional hazard assumption. [↑](#footnote-ref-15)
16. This test was performed using the *cox.zph()* command that is built into the survival package available in R. [↑](#footnote-ref-16)
17. The Weibull distribution was chosen based on a visual inspect of the fitted K-M curves and comparing the log likelihoods of the estimation of the K-M curve across several distributions. This was all carried out with built in functions in the survival R package. [↑](#footnote-ref-17)
18. Comparison between the Cox Proportional Hazard coefficients and those from the parametric estimation is done by simply adding a negative sign to the estimates from the parametric regression. [↑](#footnote-ref-18)