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 with BMI’s classified as overweight and obese drawn from the National Longitudinal Survey of Youth (1997). Our findings indicate that, on average, overweight and obese job seekers experience significantly longer spells of unemployment, other things equal. These average effects; however, differ dramatically by race and gender with Black men suffering the worse impact and White women of a normal BMI experiencing shorter unemployment spells, all else equal

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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 an accelerated failure time model with individual frailty for data selected from the National Longitudinal Survey of Youth (1997). Our results indicate that overweight individual see a 6% increase in unemployment spells while obese individuals see a 10% increase. Furthermore, we show that not all races and genders experience equal effects from BMI as White women with a normal BMI experiencing unemployment spells that are about 14% shorter than their White male counterparts and Black men of obese status experience spells 25% longer than that of White men of normal BMI. Some Hispanic men and women have shorter spells than White men in magnitude; however, there are not sufficient observations to result in statistically significant findings for these individuals.

**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)**

In this formulation, ***ho*** denotes an unknown baseline hazard function measuring the likelihood of experience the event at time ***t*** thatis 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 and weighted by the vector of estimates . A challenge involved in estimating this model is the choice of the baseline hazard function which can be addressed by assuming that the baseline hazard functions for the treated and untreated elements are proportional to each other, as is done in the Cox Proportional Hazard Model, and thus cancel in the likelihood estimation, or by specifying, *ex ante*, a parametric functional form as in the Accelerated Failure Time model. Nonparametric estimate of the survival and hazard functions for the different BMI categories used to identify treatment in this model show that the curves are approximately proportional through most of the time in the sample and thus we estimate the model using the Cox Proportional Hazard (CPH) framework.

The nature of our data includes repeated unemployment spells for several individuals which may introduction unobserved heterogeneity into the model. We control for this by assuming ‘frailty’ in model which allows the baseline hazard function to be “shifted” based on the group or cluster that is the source of the heterogeneity. For example, an individual may have low self-esteem that is not reported in the data and this may affect their search for new employment or, more importantly, may be correlated with obesity. By assuming frailty across individuals, we allow unobserved self-esteem to “shift” the baseline hazard function and thus controlling for the unobserved individual impact on the overall hazard of a given unemployment spell ending and we allow this shift to vary by individual, similar to individual random effects regression models for panel data.[[5]](#footnote-5)

Frailty is modeled by adding an intercept type term as shown in equation (4) with the term , where identifies the group or cluster to which the observation belongs (in this case the individual themselves) and denoting a matrix of individual specific parameters. We utilize the *coxme* package to estimate equation (4) shown below and this package assumes that the random effect parameter, is distributed according to the Gaussian distribution with mean zero (Therneau and Grambsch, 2000).

**(4)**

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.

**5. Data**

The data for this research are drawn from the National Longitudinal Study of Youth – 1997 (NLSY97). We use data for 1997 to 2011 because in these years the survey data includes the most comprehensive and complete set of variables for estimating our model. Unemployment spells (SPELL) are calculated using the weekly employment variable generated by the NLSY97 indicating if the respondent is employed, unemployed, or out of the labor force during each week within sample period.[[6]](#footnote-6) 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. Characteristics of the previous employer, discussed below, are matched to individuals’ unemployment spells using a unique job identifiers created by NLSY97.[[7]](#footnote-7)

Table 1 provides the names and definitions of the variables used in the analyses. Because height and weight are not collected consistently across the sample period, we interpolate the missing values.[[8]](#footnote-8) 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* (Wickham et al., 2019). 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 are classified as being overweight, and those with BMI values over 30 are classified as being obese.[[9]](#footnote-9)

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 both be influenced by unobserved individual characteristics such as self-esteem or depression. To handle the first possibility, we estimate models using both current and lagged BMI and show the results are consistent for both measures of BMI. To handle the second possible type of endogeneity, we estimate frailty models, which assume random effects for repeated spells of the same individual, to control for unobserved individual characteristics that may influence both weight and unemployment.

Control variables included in the analyses are of two types: The first describes the *personal characteristics* of the individual who experiences the unemployment spell. For these variables 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 (FamIncome),[[10]](#footnote-10) marital status (NeverMarried\*, Married, and Separated), [[11]](#footnote-11) education (LessHS\*, HS, SomeCol, CollegeGrad, and CollegePlus),[[12]](#footnote-12) self-reported health status (Good\*, Average, and Poor), and census region of residency (North East\*, North Central, South, and West).

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1** | | | | | | | | | | | |
| **Sample Summary Statistics by BMI Class1** | | | | | | | | | | | |
|  | |  | **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 of age | | 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 years 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 in the household | | 3.642 | 1.787 | 3.633 | 1.771 | 3.595 | 1.792 | 3.708 | 1.809 |
| FamIncome | 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 | | 0.217 | 0.412 | 0.221 | 0.415 | 0.199 | 0.399 | 0.228 | 0.420 |
| 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 Enrolled or completed some college | | 0.363 | 0.481 | 0.374 | 0.484 | 0.355 | 0.479 | 0.350 | 0.477 |
| CollegeGrad | =1 if Completed a 2 or 4 year degree | | 0.079 | 0.270 | 0.082 | 0.275 | 0.090 | 0.286 | 0.063 | 0.243 |
| CollegePlus | =1 if Enrolled or completed graduate degree | | 0.022 | 0.145 | 0.023 | 0.151 | 0.024 | 0.152 | 0.016 | 0.126 |
| 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 |
| GoodHealth | =1 if Self-Reported Health as Good | | 0.596 | 0.491 | 0.666 | 0.472 | 0.625 | 0.484 | 0.433 | 0.496 |
| AveHealth | =1 if Self-Reported Health as Average | | 0.297 | 0.457 | 0.257 | 0.437 | 0.285 | 0.451 | 0.382 | 0.486 |
| PoorHealth | =1 if Self-Reported Health as Poor | | 0.108 | 0.310 | 0.077 | 0.266 | 0.090 | 0.286 | 0.184 | 0.388 |
| NorthCentral | North Central Region (Midwest) | | 0.219 | 0.414 | 0.222 | 0.416 | 0.231 | 0.421 | 0.202 | 0.402 |
| NorthEast | 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 |
| SearchCount | 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 |
| Tenure | Weeks worked in current Job | | 23.784 | 54.429 | 21.689 | 50.945 | 25.195 | 57.417 | 26.165 | 57.196 |
| Exper | 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 |
| UnempRate | Regional Unemployment Rate | | 6.004 | 1.861 | 5.731 | 1.678 | 6.118 | 1.893 | 6.391 | 2.058 |
| OCC | 2-digit 1990 Census occupation code identifier (22 bins) | | | | | | | | | |
| IND | 2002 Census Industry Code identifier (18 bins) | | | | | | | | | |
| # of Unemployment Spells | | | 16,210 | | 7,662 | | 4,438 | | 4,110 | |
| # of Respondents | | | 4,992 | | 2,961 | | 2,100 | | 1,468 | |
| 1 Observations drawn from the NLSY97 for the years 1997 to 2011. Values of dummy variables not defined as =1 are assigned a value =0. Respondents may change BMI classification for different spells resulting in sub-sample count summing to more than full sample. | | | | | | | | | | |

To describe the job search behavior of a respondent during each employment spell, we create the variable (SearchCount) which is a count of the number of search methods the respondent reports having used during each unemployment spell.[[13]](#footnote-13) As these variables may vary with time, we use the value of the specific variable at the start of the specific unemployment spell since the CPH model requires time consistent controls during each specific event spell. The individual specific and 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.[[14]](#footnote-14) This score percentile, calculated by the NLSY97, is similar to the Armed Forces Qualification Test (AFQT) often used in other surveys.

The second type of independent variables are *job-specific characteristics*. These include the respondent’s tenure (Tenure) in the job immediately prior to the unemployment spell, total labor market experience (Exper) measured as the sum of all previous employment tenures, the occupation (OCC) and industry (IND) of the job immediately prior to the unemployment spell[[15]](#footnote-15), and whether that job had union representation (Union). We also include indicator variables for the reason that the unemployment spell started (Quit, Forced, Ended, Illness, Unknown\*).[[16]](#footnote-16) Finally, to capture labor market conditions we include the unemployment rate (Urate) for the Census region in which the individual resides. These monthly unemployment rates, obtained from the Saint Louis Federal Reserve Bank’s FRED website, 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 reports that the average unemployment spell lasted 11.7 weeks. There are 7,662 spells during which 2,961 respondents reported a BMI in the normal range with an average unemployment spell of 10.6 weeks, 4,438 spells experienced by 2,100 respondents who were classified as overweight at the start of the spell with an average duration of about 12.1 weeks, and the remaining 4,110 spells were experienced by 1,468 respondents who were classified as obese at the start of the spell with an average duration of of 13.4 weeks. The increase in the spell duration across BMI classification is statistically significant at the highest level between each BMI class.

Figure 1 shows the Kaplan–Meier (K-M) estimated survival curves for the full sample for each of the three BMI categories defined. The survival probability is the likelihood that an unemployment spell will

Chart

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continue given that it has lasted until that time. The median survival time, the point at which the survival probability is 50%, is shown with dashed lines. It occurs at five weeks for those in the normal BMI class, six weeks for those in the overweight class, and eight 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.[[17]](#footnote-17) We additionally see that over the relevant range, the survival curves do seem to be parallel and thus satisfying the assumptions of the CPH estimation framework.

While these factors appear to support the hypothesis that an unemployment spell is influenced by BMI classification, the values reported in Table 1 for other variables indicate that other characteristics of the survey respondents also vary by BMI class. As BMI class increases respondents are older and more likely to have a child under the age of six present in the household, have a smaller gross family income, have a lower score on the cognitive test, and are more likely to be married. The 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 who are White declines as the BMI classification increases, while the share of Black and Hispanic respondents rises. Respondents in the obese category employed more search methods than respondents in the other two categories, had longer average tenure in their previous job, and experience a longer period of overall employment.

Figures 2 and 3 show the K-M survival curves for the female and male subsamples, respectively. The impact of BMI class observed in Figure 1 appears to hold. For both men and women, the mean duration (weeks at which survival of a spell is at 50%) are the same at five, six, and eight weeks for normal, overweight, and obese classes. The key difference for males, the difference for overweight and obese is less pronounced than for females, especially in the small spell lengths.

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**6.2 Regression Analysis**

Tables 2 through 5 report coefficient estimates of the hazard functions across several specifications. In general, a negative coefficient estimate indicates that the hazard rate (likelihood) of ending an unemployment spell is decreased by the factor and a positive coefficient estimate indicates that the factor increases the hazard rate of ending the unemployment spell.

To compare assumptions about the baseline hazard model, Table 2 reports coefficient estimates from seven specifications of the Cox Proportional Hazard model in which unemployment spell length is regressed on only the variables indicating overweight and obese BMI classifications. The first three columns report statistically significant negative coefficient estimates, indicating that the that individuals who are obese at the start of the spell (column (1)) or in the year prior to the start of the spell (column (2)), respectively, experience a longer period of unemployment than individuals with normal BMI values. as indicated by a hazard ratio of about 0.81. The same is true, but to a lesser extent, for respondents with a BMI in the overweight range with a hazard ratio of about 0.89. Note that the magnitudes of the estimated effects for current and lagged BMI are very similar, which indicates that simultaneity between the BMI classification and an unemployment spell does not appear to bias the estimates. This appears to eliminate one potential cause of endogeneity. However, the two specifications differ in that the model using the lagged BMI classification has a slightly better fit to the data.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Models of Unemployment Duration with only BMI Classifications** | | | | | | | |
| Coefficient Estimates for the Cox Proportional Hazard and AFT Models | | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 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 |
| 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. Hazard ratios are obtained via exp(coefficient). | | | | | | | |

A second possible cause of endogeneity between the BMI classification and unemployment spells is that both may be influenced by unobserved individual characteristics. We address this by assuming individual frailty in the model which allows the base hazard to differ by individual. As explained above, this individual-specific control is similar to that in a random effects regression model. The results of the frailty model, reported in column (3) of Table 2 for BMI classifications measured at the start of the spell, show an increase in the magnitude of the effect while retaining the statistical significance: The hazard ratio for an overweight individual falls to 0.86 and that for an obese individual falls to 0.76.

Another concern is that the model may be mis-specified. Specifically, the assumption of the Cox Proportional Hazard model that coefficients impact the baseline hazard proportionally (so that the survival curves are parallel) may be violated. This assumption of proportionality can be tested using a Schoenfeld residual test. The results of tests using the estimates from columns (1), (2), or (3) reject the null hypothesis of proportional hazards for the obese coefficient.[[18]](#footnote-18) 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) as well as consideration of several alternatives, we use a Weibull distribution to estimate the model with current BMI classification (column (4)), lagged BMI (column (5)), lagged BMI with individual frailty (column (6)), and lagged BMI with individual frailty (column (7)).[[19]](#footnote-19)

The coefficient estimates for Overweight and Obese reported in Table 2 are statistically significant and indicate that unemployment duration is longer for individuals with an overweight BMI classification compared to individuals with normal BMI and even longer for individuals with an obese BMI classification.[[20]](#footnote-20) Furthermore, the hazard ratio for overweight individuals in column seven is about 0.76 and for obese the hazard ratio is about 0.63.

Based on the results reported in Table 2, we estimate further specifications of the AFT model assuming a Weibull baseline hazard function with individual frailty. In Table 3 we report coefficient estimates from specifications of as additional covariates are added. Columns (1), (3), and (5) use the current BMI classification while columns (2), (4), and (6) use the lagged BMI classification.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 3: AFT Models of Unemployment Duration**  **with Additional Covariates** | | | | | | |
|  | (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) |
| FamIncome | -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) |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 3: AFT Models of Unemployment Duration with Additional Covariates (cont.)** | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| 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) |
| Tenure | 0.0010\*\*\* | 0.0010\*\*\* | 0.0010\*\*\* | 0.0010\*\*\* | -0.0004\* | -0.0005\* |
|  | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Experience | 0.0003\*\* | 0.0003\*\* | 0.0001 | 0.0001 | 0.0000 | -0.0000 |
|  | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| AveHealth | -0.0039 | -0.0019 | -0.0101 | -0.0078 | -0.0104 | -0.0078 |
|  | (0.0180) | (0.0181) | (0.0178) | (0.0179) | (0.0177) | (0.0178) |
| PoorHealth | -0.0432 | -0.0404 | -0.0525 | -0.0499 | -0.0566\* | -0.0545\* |
|  | (0.0276) | (0.0276) | (0.0272) | (0.0273) | (0.0271) | (0.0271) |
| NorthCentral | -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) |
| 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) |
| UnempRate |  |  | 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) |
| SearchCount |  |  | 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))). | | | | | | |

Columns (1) and (2) report estimates for specifications including only the set of individual-specific covariates, columns (3) and (4) report estimates when job-specific covariates are added without controlling for occupation or industry, and columns (5) and (6) report estimates when we add fixed effects for occupation and industry. In all of the specifications, the unemployment spell of an obese individual 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 approximately 1.6 weeks longer than an individual with a normal BMI value, all else equal. For an overweight individual, the magnitude of the estimated effect of the BMI classification is more sensitive to the specification with the impact ranging between 5 and 6%. This translates into 5 to 7 days greater unemployment duration for an overweight individual compared to a normal weight individual. However, the effect is only statistically significant for the lagged BMI classification.

The estimated effects of the other covariates are relatively stable in both magnitude and statistical significance across the specifications in Table 3, with some larger changes being observed for the job-specific variables when occupation and industry are controlled for. Among those that are significant we observe that women have a shorter duration compared to men, on average, while age increases the duration of unemployment spells. Similar to what we have seen in our descriptive figures, unemployment spells for Black individuals tend to be significantly longer than those for Whites, while the difference in unemployment duration between Hispanic and White respondents is not statistically significant. Having a higher gross family income, greater educational attainment, and higher cognitive skills all shorten the duration of an unemployment spell.

The only instance in which coefficient estimates change sign across specifications is in the estimated effect of job tenure. Having longer tenure in the job just prior to unemployment has a small positive effect on the duration of the subsequent unemployment spell except when we control for occupation and industry. The inclusion of these fixed effects causes the estimated effect of job tenure to become negative. However, the size of the negative effect is very small making it economically insignificant.

Another change in estimates caused by the inclusion of the industry and occupation fixed effects is the statistical significance of self-reported poor health, which becomes statistically significant when we control for occupation and industry. Interestingly, we observe that , however, that poor health shortens an individual’s unemployment spell. It is important to keep in mind that an individual who leaves a job and takes time off (that is, without searching for work) due to an illness, is not included in our sample until they start searching for work again. This may lead us to observe artificially short search periods. In addition, respondents in poor health may have a greater need for employment-related health insurance, leading to a shorter unemployment spell.

Finally, region also affects the length of unemployment duration, with respondents living in the Northeast (the reference category) having the longest duration of unemployment and those in the West having the shortest duration. The latter observation is consistent with the economic expansion experienced in many western states during the survey years.

Focusing on the last two columns of Table 3 we see that higher unemployment rates in the respondent’s region extends the duration of unemployment, as expected. The interpretation of the effects across the different causes for job separation are difficult to directly interpret because we cannot know the reasons for separation for those observations coded as unknown. However, we can compare the relative magnitudes for the various causes relative to the reference category. We observe that a person who was fired or whose job ended experiences relatively large increases in unemployment duration compared to the reference category in which the job ending is unknown, while quitting the prior job has a smaller positive impact on the duration of unemployment compared to respondents for whom the reason for job ending is unknown. We see a similar estimate, albeit not statistically significant, when an unemployment spell is started due to illness as we did with poor self-reported health.

Finally, we find that the more search methods an individual uses, the longer the duration of unemployment. However, this estimate may be biased because the duration of unemployment may be endogenous with the number of search methods if an individual utilizes more search methods the longer an unemployment spell lasts. Interestingly, we also observe that union representation does not impact the duration of the subsequent unemployment spell, even in specifications (3) and (4) when occupation and industry fixed effects are not included.

**6.3 Analysis of Subgroup Effects**

In the K-M survival graphs above, we illustrate how the BMI impact on unemployment duration varies by sex, race, and Hispanicity. We now investigate effects for these groups in the AFT model. Because the limited number of observations in some groups does not permit a separate analysis of each group, we instead use interaction variables to identify the effects of obesity and overweight status for men and women who are White, Black, and Hispanic. Table 4 reports the estimated effects of the sex, race, and Hispanicity interactions. For the estimates in Table 4 we use the specification with lagged BMI in the full model with occupation and industry controls similar to column (6) in Table 3.

**NEW TABLE 4 HERE AND REVISED DISCUSSION BELOW**

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.

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. An alternative method to identify unemployment spells is to use the responses to the questions indicating the start and stop dates of employment. However, if the respondent is still employed the interviewer is instructed to insert the interview date creating an error in coding an unemployment spell. Additionally, using these questions makes the measurement of spells across calendar years problematic and there is no indication if the respondent is unemployed or out of the labor force. [↑](#footnote-ref-6)
7. In the weekly data, unemployment spells that are ended by employment are indicated using a unique job id. [↑](#footnote-ref-7)
8. Height and weight are reported in each survey year; however, there are missing values for various respondents across the panel. [↑](#footnote-ref-8)
9. Centers for Disease Control and Prevention (2017). Although we remove underweight individuals (BMI < 18.5) because such a low BMI may be an indication of illness, our estimates are robust to this removal. [↑](#footnote-ref-9)
10. The reported gross family income is adjusted using the inverse hyperbolic sine transformation, which is similar to using the natural log transformation but allows values 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. Students that either dropped out of college prior to graduation or are still enrolled but have not yet graduated are classified as SomeCol. Students who have graduated from a 2-year or 4-year degree program and are not currently enrolled are classified as CollegeGrad and students who attended college for more than four years are classified as CollegePlus whether graduated, dropped out, or still enrolled. [↑](#footnote-ref-12)
13. 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-13)
14. Reported in the initial interview. [↑](#footnote-ref-14)
15. The occupation is based on the first two-digits of 1990 Census Occupation Codes resulting in 22 different occupation classifications. The industry is based on the first two digits of the 2002 three-digit Census Industry Code resulting in 18 different industry classifications. [↑](#footnote-ref-15)
16. There are several missing or skipped observations for this question, so the category UNKNOWN is used to capture these events. [↑](#footnote-ref-16)
17. 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 a violation of the proportional hazard assumption. [↑](#footnote-ref-17)
18. This test was performed using the *cox.zph()* command that is built into the survival package available in R. [↑](#footnote-ref-18)
19. 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 functions available in the R survival package. [↑](#footnote-ref-19)
20. Comparison between the estimates from the Cox Proportional Hazard model and those from the parametric model is done by simply adding a negative sign to the estimates from the parametric regression. [↑](#footnote-ref-20)