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 by estimating 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. The average effects; however, differ dramatically by race and gender with women experiencing longer spells across BMI classifications and Black women seeing longer unemployment spells compared to White women of similar BMI. Conversely, men see no impact on unemployment spells by BMI; however, Black men experience longer spells than White men, all else equal

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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 and appropriate policy design requires that we better understand the factors of such spells. To contribute to our understanding of the relationship between obesity and unemployment, we examine the impact of obesity on the duration of unemployment spells and further investigate the impact by sex and race.

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 Cox Proportional Hazard (CPH) model with individual frailty for data selected from the National Longitudinal Survey of Youth (1997). Our results indicate that overweight individual see a 5% increase in unemployment spells while obese individuals see a 11% increase. Furthermore, we show that not all races and genders experience equal effects from BMI as White women classified as overweight experience unemployment spells about 12% longer than White women of normal BMI (the baseline). Likewise, White women classified as obese experience spells that are about 19% longer than the baseline. For Black women, those with a normal BMI experience the largest impact on unemployment spells seeing spells that last about 29% longer than the baseline. The duration for Black women classified as overweight or obese are shorter compared to Black women with a normal BMI and are about the same as the impact experienced by White women of the same BMI classification. For men, however, BMI classification has no impact on unemployment spell duration for any race; however, Black men, in general, all experience unemployment spells about 16% longer than White 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**

To test whether obesity has a significant differential impact on unemployment duration while controlling for unobserved individual-specific effects, we estimate the hazard model, shown below, and calculate the probability that an unemployment 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” or end of spell at time ***t*** thatis shared by all and is only a function of time (that is, how long the spell has lasted up to this point in time). This baseline hazard is multiplied by the term incorporating individual characteristics, measured by the vector and weighted by the vector . 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 observations are proportional to each other, as is done in the Cox Proportional Hazard (CPH) 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 estimates 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 framework.[[5]](#footnote-5)

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 survey but affects their search for new employment or, more importantly, may be correlated with obesity. By assuming frailty across individuals, we allow self-esteem, or any other unobserved individual characteristic, to ‘shift’ the baseline hazard function thus controlling for the unobserved individual impact on the overall hazard of a given unemployment spell ending. We allow this shift to vary by individual comparable to individual random effects regression models for panel data.[[6]](#footnote-6)

Specifically, we add the term , to the hazard function, shown in equation (4), where identifies the group or cluster to which the observation belongs (in this case the individual themselves) and denotes a matrix of individual specific parameters with 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 the baseline hazard is modified by 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 at time *t* (given it has lasted to time *t*) to be smaller than the baseline hazard, all else equal, implying that the unemployment spell has a higher likelihood of continuing (sometimes referred to as increased survivability). A hazard ratio larger than one (generated by a positive coefficient estimate) implies that the increase in 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 as these represent the most comprehensive and complete set of variables needed to estimate 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.[[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 a spell ends by the respondent becoming employed. Spells that end by the respondent leaving the workforce are removed from the data and reentry to the labor force starts a new unemployment spell. Characteristics of the previous employer, discussed below, are matched to individuals’ unemployment spells using a unique job identifier created by NLSY97.[[8]](#footnote-8)

Table 1 provides the names and definitions of the variables used in the analysis. Because height and weight are not collected consistently and contain errors across the sample period for every respondent, we are required to fill in the missing values by first removing any observation larger than 2.5 standard deviations of the mean for each individual.[[9]](#footnote-9) With the remaining observations, the average height is assumed as the height to the respondent for the entire period of the sample and missing weights are determined by interpolation 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. According to 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.[[10]](#footnote-10)

Control variables included in the analyses are of two types: The first describes the *personal characteristics* of the individual who experiences the unemployment spell and the second describe the *job specific characteristics* for the job immediately preceding the spell. For the personal characteristics we link the annual reported values of the individual characteristics to the year in which the unemployment spell started, and these values are assumed constant for the duration of that spell. Besides obesity, we include age (Age), sex (Male\*, Female), race (White\*, Black, and Hispanic), marital status (NeverMarried\*, Married, and Separated),[[11]](#footnote-11) education (LessHS\*, HS, SomeCol, CollegeGrad, and CollegePlus),[[12]](#footnote-12) 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),[[13]](#footnote-13) 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. Also included are self-reported health status (Good\*, Average, and Poor), census region of residency (NorEst, NorCen, South, and West\*), and a measure of job search behavior of a respondent during each employment spell measured by the variable (SearchCT) which is a count of the number of search methods the respondent reports having used during each unemployment spell.[[15]](#footnote-15)

The job specific characteristics include 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[[16]](#footnote-16), and whether that job had union representation (Union). We also include indicator variables denoting the reason the unemployment spell started (Quit, Forced, Ended, Illness, Unknown\*)[[17]](#footnote-17) and include the unemployment rate (Urate) for the Census region in which the individual resides to capture overall labor market tends. 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.

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1** | | | | | | | | | |
| **Summary Statistics for Full Sample and by BMI Classification** | | | | | | | | | |
|  |  | 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 |
| Male\* | =1 if Male | 0.513 | 0.500 | 0.510 | 0.500 | 0.589 | 0.492 | 0.434 | 0.496 |
| 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 |
| NeverMarried\* | =1 if Currently Married | 0.842 | 0.365 | 0.879 | 0.326 | 0.828 | 0.378 | 0.787 | 0.409 |
| Married | =1 if Never Married | 0.125 | 0.331 | 0.092 | 0.289 | 0.137 | 0.343 | 0.173 | 0.379 |
| Separated | =1 if Separated, Divorced, or Widowed | 0.033 | 0.179 | 0.029 | 0.167 | 0.036 | 0.185 | 0.039 | 0.194 |
| Child6 | =1 if Child aged 6 or less present in home | 0.442 | 0.779 | 0.372 | 0.742 | 0.440 | 0.753 | 0.574 | 0.854 |
| GFinc | Total Gross Family Income (IHS) | 10.475 | 2.452 | 10.554 | 2.353 | 10.450 | 2.551 | 10.353 | 2.515 |
| HH\_Size | Total size of household | 3.642 | 1.787 | 3.633 | 1.771 | 3.595 | 1.792 | 3.708 | 1.809 |
| 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 |
| Score | Percentile Rank on ASVAB Exam | 39.152 | 28.691 | 41.669 | 29.462 | 38.428 | 28.456 | 35.240 | 26.962 |
| 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 |
| 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 |
| West\* | West Region | 0.214 | 0.410 | 0.221 | 0.415 | 0.217 | 0.412 | 0.197 | 0.398 |
| 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 |
| Urate | Regional Unemployment Rate | 6.004 | 1.861 | 5.731 | 1.678 | 6.118 | 1.893 | 6.391 | 2.058 |
| 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 |
| Unknown\* | =1 if Job ending cause unknown | 0.940 | 0.238 | 0.941 | 0.235 | 0.938 | 0.242 | 0.940 | 0.238 |
| 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 |
| Forced | =1 if Job ended by being fired | 0.007 | 0.084 | 0.006 | 0.080 | 0.007 | 0.086 | 0.008 | 0.091 |
| Illness | =1 if Job ended voluntary | 0.001 | 0.030 | 0.001 | 0.023 | 0.001 | 0.034 | 0.001 | 0.038 |
| Quit | =1 if Job ended due to illness | 0.027 | 0.161 | 0.027 | 0.161 | 0.027 | 0.162 | 0.026 | 0.160 |
| Union | =1 if Job before gap had union | 0.019 | 0.137 | 0.015 | 0.123 | 0.023 | 0.148 | 0.022 | 0.147 |
| OCC | 2-digit 1990 Census Occupation Code Identifier (22 bins) | | | | | | | | |
| IND | 2002 Census Industrial Code Identifier (18 bins) | | | | | | | | |
| # of Unemployment Spells | | 16,210 | | 7,662 | | 4,438 | | 4,110 | |
| # of Unique Respondents | | 4,992 | | 2,961 | | 2,100 | | 1,468 | |
| 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 respondents summing to more than full sample. Variables with asterisk indicate reference variables for dummy variables | | | | | | | | | |

**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 reported by 2,961 respondents with a BMI classified in the normal range with an average unemployment spell of 10.6 weeks, 4,438 spells reported 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 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 non-parametric Kaplan–Meier (K-M) survival curves for the full sample for each of the three BMI categories for the first 30 weeks.[[18]](#footnote-18) The survival probability is the likelihood that an unemployment spell continues given that it has lasted until that time and the median survival time, the point at which the survival probability is 50%, is shown with dashed lines. The mean survival 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 each class over most weeks shown and the survival curves appear parallel across most weeks as required by CPH estimation framework.

Figures 2 and 3 show the K-M survival curves for female and male subsamples, respectively. The impact of BMI class observed in Figure 1 appears to hold for each of the sexes as well. For both men and women, the median survival times are the same as the full sample at five, six, and eight weeks for normal, overweight, and obese classes. The key difference for males is that the difference between overweight and obese is less pronounced than for females, especially for unemployment spells lasting longer.

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While these figures appear to support the hypothesis that an unemployment spell is influenced by BMI classification, the values reported in Table 1 for other variables and previous research indicate that other characteristics of the survey respondents also vary by BMI class. As one moves across BMI classes, respondents tend to be older, more likely to have a child under the age of six present in the household, have a smaller gross family income, have a lower ability score, and more likely to be married. The percentage of respondents with less than high school, high school or equivalent, and some college across the BMI categories while the percentage that have more than four years of college decreases across the BMI categories. The percentage of respondents who are White declines as one moves to higher BMI classifications, while the share of Black and Hispanic respondents rises. Respondents in the obese category utilized more search methods than respondents in the other two categories, had longer average tenure in their previous job, and experience longer periods of overall employment as measure by experience.

**6.2 Regression Analysis**

Tables 2 through 4 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 lower compared to the baseline hazard and a positive coefficient estimate indicates that the factor increases the hazard rate of ending the unemployment spell relative to the baseline.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 2** | | | | |
| **Estimated Hazard Ratios with Current and Lagged BMI Classification with and with Frailty** | | | | |
|  | (1) | (2) | (3) | (4) |
| Overweight | -0.1161 \*\*\* | -0.1338 \*\*\* | -0.1538 \*\*\* | -0.1808 \*\*\* |
|  | (0.0189) | (0.0191) | (0.0231) | (0.023) |
| Obese | -0.2086 \*\*\* | -0.2108 \*\*\* | -0.2989 \*\*\* | -0.2981 \*\*\* |
|  | (0.0194) | (0.0198) | (0.0255) | (0.0258) |
| Variable Coef. Std. Dev. |  |  | 0.4519 | 0.4458 |
| Spells (Observations) | 16,210 | 15,800 | 16,210 | 15,800 |
| AIC | 281732.00 | 273790.50 | 280616.70 | 272736.00 |
| BIC | 281747.40 | 273805.80 | 293503.60 | 285107.30 |
| Log Likelihood | -140864.00 | -136893.20 | -138633.30 | -134754.60 |
| Significance Levels: ^=10%, \*=5%, \*\*=2.5%, \*\*\* 1%. Frailty modeled with Gaussian distribution and models estimated with *coxph* and *coxme* command in R. Standard errors in parathesis. Intercept SD indicates the standard deviation of the mixed effect constant terms estimated according to frailty across individual respondent (ID) and loglikelihood testing the significance of the random effects are all significant at the highest level. | | | | |

Table 2 shows the model estimated with only the different BMI categories. Column (1) shows the estimates of the Cox Proportional Hazard model and shows that a respondent classified as overweight at the beginning of a spell can expect to experience a 12% longer unemployment spell, all else equal, compared to a respondent who is of normal weight. With the average spell being about 11.7 weeks, the overweight respondent can expect to experience unemployment for a total of 13.1 weeks. The respondent that is obese can expect to experience unemployment for about 21% longer or about 2.5 weeks more than an individual of normal BMI.

Beyond the previously discussed endogeneity caused by repeated spells by a given individual, one may be concerned that BMI, specifically weight, is related to the length of an unemployment spell. To satisfy the assumptions of the CPH model, we use the BMI classification at the start of the unemployment spell, and this remains constant for the duration of the spell leading to a lower likelihood of endogeneity bias. To support this claim, we also estimate the simple model using the BMI classification for the respondent in the year prior to the start of the unemployment spell. The stability of the estimates shown in column (2) indicate this potential source of endogeneity should not be a problem in this context. Column (3) tests the second source of possible endogeneity by estimating the model with frailty across individuals. As discussed previously, we allow for there to be a unique term which modifies the baseline hazard for all spells experience by that individual to account for unobserved variation that is specific to the individual respondent.

The magnitude of the BMI classification effect grows slightly with overweight individuals now experience a 15% increase in duration while an obese individual experiences a nearly 30% increase in the unemployment spell, all else equal.[[19]](#footnote-19) Among the diagnostic statistics shown, the standard deviation for the individual specific constant term is shown to give a sense of the variation among individuals in the dataset. This value can be interpreted as an individual located one standard deviation from the average respondent will experience a baseline hazard about 40% different from the average individual’s baseline hazard. As the “average individual” is not clearly defined, we simply show this result as a diagnostic to ensure the inclusion of extra controls are not impacting the frailty in some unforeseen way. Finally, we also use the lagged BMI classification combined with the individual frailty in column (4) and the results are consistent with those in column (3) indicating the current BMI classification is sufficiently free of endogeneity bias.

Table 3 reports coefficient estimates from specifications with additional controls for individual, market, and job specific effects. Columns (1) and (2) show the estimates from adding individual specific characteristics without and with frailty across individuals. Since we again reject the null hypothesis of no frailty effects, columns (3) and (4) maintain the assumption of frailty across individuals with column (3) adding market related measures and column (4) including job specific effects, mostly via fixed industry and occupational effects.

[Insert Table 3]

The inclusion of individual specific controls in columns (1) and (2) slightly reduce the impact of the BMI classification with regards to unemployment spells with overweight individuals seeing an extension of their unemployment spells by about 5% while obese individuals see an increase of between 11% and 12%, depending on if frailty is assumed or not. Adding market and job specific controls does not change the magnitude of the BMI classification effects significantly, but for overweight individuals, the statistical significance decreases to between five and ten percent in columns (3) and (4). The effect for obese individuals remains statistically significant at the highest level.

The estimated effects of the other covariates are relatively stable in both magnitude and statistical significance across the specifications in Table 3, with some changes observed for regional indicators and the controls measuring the reason the spell started once occupation and industry are controlled for. We observe that women have a shorter duration compared to men, on average, while age increases the duration of unemployment spells. Unemployment spells for Black individuals tend to be significantly longer than those for Whites (15 to 20% longer), while the difference in unemployment duration between Hispanic and White respondents is not statistically significant. Being married, having a higher gross family income, greater educational attainment (compared to no high school diploma), higher cognitive skills, and more years of experience prior to the start of the spell all shorten the duration of an unemployment spell by various degrees. Residing in the North Central region increases the duration by about 6% compared to those in the West region and residing in the Northeast region increases the duration of an unemployment spell by about 12% compared to the West region. The remaining controls including the presence of children under the age of 6, the household size and the self-reported measure of health all have no statistically significant effect.

The controls added in column (3) only slightly impact the existing controls with the impact of age getting smaller and married losing significance. The largest impact on existing controls come in the regional controls where durations in the North Central and Northeastern regions increase in magnitude and those residing in the Southern region now see a statistically significant increase in unemployment spell of about 8%. The impact from the added controls mostly follow expectations as a higher unemployment rate leads to a higher unemployment duration as do cases where the spell is started by either forced separation, a job ending, or even the respondent quitting with the latter leading to the smallest impact of the three. The fact that more search methods increase the duration of unemployment is not surprising if one recalls that this value is reported either after the spell has ended or the respondent is interviewed during an existing spell so the estimate is likely measuring the idea that as an unemployment spell lasts longer, additional search methods will be employed. Adding union membership and occupation and industry fixed effects in column (4) only slightly lowers the magnitude of the impact of the obese BMI classification and only impacts the magnitudes of the separation measures and causes tenure to become very small and statistically insignificant. The last row of information in Table 3 indicates that the standard deviation of the individual specific intercept terms only changes slightly with the addition of more controls.

**6.3 Analysis of Subgroup Effects**

It is well known that men and women have different labor market experiences and that the race of the respondent may also contribute to different experiences. Table 4 shows the estimates for model estimated on sub-samples of women and men separately with interactions between the BMI classification and race. In all cases the models are estimated assuming frailty across individuals and include the full set of controls including occupation and industry fixed effects. Furthermore, the use of the subsamples and variable interactions do not significantly alter the distribution of the individual specific effects as indicated by the variable coefficient standard deviation.

[Insert Table 4]

The first columns show that, all else equal, women classified as overweight see no statistical difference in their unemployment spell duration compared to women classified as normal weight. Women classified as obese, however, see a 13% increase in their unemployment spell duration compared to women of other classifications. We also see that Black women see a significant increase in their unemployment spell of about 21% or about 2.5 compared to White women and Hispanic women still see no statistical difference in the duration of their unemployment spell, all else equal.

The second column under the female heading interacts the racial identifier with the BMI class and sheds some additional light on how different women are impacted by their BMI classification and race. The duration of overweight White women returns to statistical significance, compared to the White women classified with a normal BMI, and increases by about 12%. White women classified as obese see their spell duration increase slightly to about 19%. The largest and most unexpected changes come from Black women. A Black woman with a BMI classification of normal sees a 29% increase in their unemployment spell, or almost 3.5 weeks longer, than their White counterpart, also with a BMI classification of normal. Surprisingly, however, Black women classified as overweight or obese see a shorter unemployment spell compared to Black women with a normal BMI classification. Compared to a White women of normal BMI class, a Black women classified as overweight experience an unemployment spell about 12% longer and Black women classified as obese experience a spell about 16% longer. As before, being Hispanic has no impact on unemployment spell regardless of BMI classification.

For men, the last two columns of Table 4 show a very different set of effects. For White men, there is no statistically significant impact on unemployment spell by BMI and if the magnitudes were to be believed, overweight and obese men would experience the same impact of unemployment spells lasting about 4% longer than White men with a normal BMI. Black men with a normal BMI experience unemployment spells about 16%, are just under two weeks, longer than White men with a normal BMI. This impact on Black men is constant across all BMI classes showing that similar to White men, BMI classification has no statistically significant impact on unemployment duration. Taking the results of columns three and four, it seems that only race (excluding Hispanic) and region are the primary determining factors for the duration of unemployment spells for men.

There are also some interesting comparisons between men and women among the other control variables as well. While unemployment durations increase with age, they do so at a slower rate for women than for men. Additionally, a women’s unemployment duration is shorted with higher gross family income, but men see no impact from income. Likewise, while household size has no impact on women’s duration, men see a slight, but statistically significant, increase in their unemployment duration. This could indicate that men with larger families are more selective with job offers than men with smaller families. Education also has different impacts across the sexes. While men and women see similar results from a high school diploma or its equivalent compared to no degree (about 10% shorter), having some college or a college degree greatly reduces a male’s unemployment spell (25% and 18% respectively) while helping women relatively less (18% and 11%). The impact from education beyond a bachelor’s degree seems to hurt women by increasing the unemployment duration while helping men by decreasing their unemployment duration; however, the estimates are not statistically significant.

Another difference is that women seem to be less helped by previous experience and seem to not be impacted by how the unemployment spell started unless it is started with the women quitting and while the effect is rather large at 14%, it is only just statistically significant. Men; however, see longer durations if the job separation is forced (about 44% longer) or if the job ends (23% longer) and men in all three regions see longer durations compared to men in the West region. Only women in the Northeast region see any special regional impact on their unemployment spell.

**7. Discussion**

Prior studies find that obesity causes significantly higher unemployment among American workers while others have suggested that it is unobserved characteristics of the individual rather than obesity cause these employment penalties (e.g., Lindeboom et al., 2010). Using data from the National Longitudinal Study of Youth (1997), 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 4% longer than those with normal BMI and those classified as obese spend about 11% more time unemployed, all else equal. In terms of weeks, this equates to slightly less than one week for those overweight and slightly more than one week for those that are obese.

By splitting the sample into male and female subsamples and interacting the BMI classification with race we show that White women with an overweight BMI classification experience unemployment spell about 12% longer than White women with a normal BMI and obese White women experience unemployment spells about 20% than their normal BMI colleges. Furthermore, a Black woman with a normal BMI sees the largest BMI effect on unemployment spell by experiencing spells that are about 29% longer, or about 3 weeks longer, than White women with normal BMI. Additionally, for Black women, being overweight reduces the unemployment spells compared to Black women with a normal BMI to about 12% or only 1.5 weeks longer than the baseline (White women with a normal BMI) and obese Black women also enjoy a shorter duration compared to Black women with normal BMI, but still experience longer unemployment spells compared to the baseline.

White men do not seem to be impacted by BMI classification as no estimates are statically significant for White men implying they all experience roughly the same baseline hazard regardless of BMI. Black men, on the other hand, all suffer increased unemployment spells of about 16%, or about 1.75 weeks longer, than White males and, unlike with Black women, this impact on Black men is constant across BMI classification. This seems to indicate that with men, race and region are the dominate factors impacting unemployment duration while BMI classification has no statistical impact at all. With both men and women, Hispanic respondents see no impact by either their race or BMI classification.

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| --- | --- | --- | --- | --- |
| **Table 3** | | | | |
| **Estimated CPH Model with Frailty by Individual with Controls** | | | | |
|  | (1) | (2) | (3) | (4) |
| Overweight | -0.0482 \* | -0.046 \* | -0.0409 ^ | -0.0413 ^ |
| (0.0191) | (0.0228) | (0.0226) | (0.0226) |
| Obese | -0.1048 \*\*\* | -0.1266 \*\*\* | -0.1131 \*\*\* | -0.1061 \*\*\* |
| (0.0203) | (0.0257) | (0.0254) | (0.0253) |
| Female | 0.053 \*\* | 0.0732 \*\*\* | 0.0624 \*\* | 0.0654 \*\* |
| (0.0167) | (0.0219) | (0.0216) | (0.0221) |
| Age | -0.0675 \*\*\* | -0.0665 \*\*\* | -0.0413 \*\*\* | -0.045 \*\*\* |
| (0.0038) | (0.0044) | (0.0049) | (0.0049) |
| Black | -0.1572 \*\*\* | -0.203 \*\*\* | -0.1805 \*\*\* | -0.178 \*\*\* |
| (0.0211) | (0.0282) | (0.0279) | (0.0278) |
| Hispanic | -0.0106 | -0.014 | -0.02 | -0.0163 |
| (0.0232) | (0.0305) | (0.03) | (0.0299) |
| Married | 0.0554 \* | 0.0583 ^ | 0.0488 | 0.0504 ^ |
| (0.0259) | (0.0309) | (0.0306) | (0.0306) |
| Separated | -0.0545 | -0.0822 | -0.0516 | -0.0392 |
| (0.0456) | (0.0547) | (0.0544) | (0.0544) |
| Child6 | 0.0038 | 0.0098 | 0.0046 | 0.0058 |
| (0.0126) | (0.0148) | (0.0147) | (0.0147) |
| GFinc | 0.0103 \*\* | 0.0121 \*\* | 0.0128 \*\* | 0.0148 \*\*\* |
| (0.0034) | (0.0039) | (0.0039) | (0.0039) |
| HH\_Size | -0.0057 | -0.0094 | -0.0083 | -0.0108 ^ |
| (0.0053) | (0.0062) | (0.0062) | (0.0062) |
| HS | 0.0658 \*\* | 0.0869 \*\* | 0.0852 \*\* | 0.0963 \*\*\* |
| (0.0228) | (0.0285) | (0.0283) | (0.0282) |
| SomeCol | 0.169 \*\*\* | 0.1986 \*\*\* | 0.2018 \*\*\* | 0.2113 \*\*\* |
| (0.0248) | (0.0314) | (0.0311) | (0.031) |
| CollegeGrad | 0.1119 \*\* | 0.1106 \* | 0.1123 \* | 0.1413 \*\* |
| (0.0384) | (0.0465) | (0.0462) | (0.0467) |
| CollegePlus | 0.0117 | -0.0085 | 0.002 | -0.0034 |
| (0.0613) | (0.0727) | (0.0722) | (0.073) |
| Score | 0.0036 \*\*\* | 0.0043 \*\*\* | 0.0044 \*\*\* | 0.0043 \*\*\* |
| (0.0004) | (0.0005) | (0.0005) | (0.0005) |
| Tenure | -0.0012 \*\*\* | -0.0012 \*\*\* | -0.0013 \*\*\* | 0.0002 |
| (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Experience | 0.0004 \*\*\* | 0.0001 | 0.0003 \* | 0.0004 \*\*\* |
| (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| AvgHealth | -0.0254 | -0.0154 | -0.0085 | -0.0087 |
| (0.0181) | (0.0209) | (0.0207) | (0.0207) |
| PoorHealth | -0.0335 | -0.0088 | 0.0025 | 0.0033 |
| (0.0268) | (0.0315) | (0.0313) | (0.0312) |
| NorthCentral | -0.0616 \* | -0.0611 ^ | -0.1006 \*\* | -0.1064 \*\*\* |
| (0.0251) | (0.0327) | (0.0324) | (0.0323) |
| NorthEast | -0.1228 \*\*\* | -0.1479 \*\*\* | -0.2209 \*\*\* | -0.2242 \*\*\* |
| (0.0274) | (0.0356) | (0.0356) | (0.0355) |
| South | -0.0258 | -0.0346 | -0.089 \*\* | -0.0933 \*\* |
| (0.0227) | (0.0295) | (0.0295) | (0.0294) |
| UnempRate |  |  | -0.0736 \*\*\* | -0.0756 \*\*\* |
|  |  | (0.0066) | (0.0066) |
| SearchCount |  |  | -0.0592 \*\*\* | -0.0566 \*\*\* |
|  |  | (0.0047) | (0.0047) |
| Forced |  |  | -0.478 \*\*\* | -0.2471 \* |
|  |  | (0.101) | (0.1036) |
| Ended |  |  | -0.4173 \*\*\* | -0.2032 \*\*\* |
|  |  | (0.0545) | (0.0582) |
| Illness |  |  | -0.0432 | 0.2144 |
|  |  | (0.2734) | (0.2753) |
| Quit |  |  | -0.3432 \*\*\* | -0.1222 \* |
|  |  | (0.0533) | (0.0565) |
| Union |  |  |  | 0.0194 |
|  |  |  | (0.0663) |
| Occupation Fixed Effects | No | No | No | Yes |
| Industry Fixed Effects | No | No | No | Yes |
| Variable Coef. Std. Dev. |  | 0.4013 | 0.3853 | 0.3777 |
| Significance Levels: ^=10%, \*=5%, \*\*=2.5%, \*\*\* 1%. Frailty modeled with Gaussian distribution and models estimated with *coxph* and *coxme* command in R. Standard errors in parathesis. Intercept SD indicates the standard deviation of the mixed effect constant terms estimated according to frailty across individual respondent (ID) and loglikelihood testing the significance of the random effects are all significant at the highest level. | | | | |

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| --- | --- | --- | --- | --- |
| **Table 4** | | | | |
| **Estimates of CPH Sex Subsamples with Frailty Across Individuals and Full Controls** | | | | |
|  | Female Only | | Male Only | |
| Overweight | -0.0447 | -0.1255 \* | -0.031 | -0.0469 |
| (0.0342) | (0.0526) | (0.0305) | (0.0432) |
| Obese | -0.1295 \*\*\* | -0.1963 \*\*\* | -0.0709 ^ | -0.0434 |
| (0.0352) | (0.054) | (0.0372) | (0.0547) |
| Age | -0.0334 \*\*\* | -0.0342 \*\*\* | -0.0577 \*\*\* | -0.058 \*\*\* |
| (0.0071) | (0.0071) | (0.007) | (0.007) |
| Black | -0.2102 \*\*\* | -0.2856 \*\*\* | -0.1486 \*\*\* | -0.1564 \*\* |
| (0.0401) | (0.0525) | (0.0392) | (0.05) |
| Black X Overweight |  | 0.1669 \* |  | 0.0562 |
|  | (0.0764) |  | (0.0679) |
| Black X Obese |  | 0.1293 ^ |  | -0.0444 |
|  | (0.076) |  | (0.0821) |
| Hispanic | -0.0187 | -0.0646 | -0.017 | 0.0009 |
| (0.0435) | (0.0572) | (0.0417) | (0.0601) |
| Hispanic X Overweight |  | 0.0989 |  | -0.0124 |
|  | (0.092) |  | (0.0818) |
| Hispanic X Obese |  | 0.1017 |  | -0.0562 |
|  | (0.0919) |  | (0.0935) |
| Married | 0.0182 | 0.0188 | 0.0704 | 0.0711 |
| (0.0405) | (0.0405) | (0.0483) | (0.0483) |
| Separated | -0.1203 ^ | -0.1111 | 0.0397 | 0.0378 |
| (0.0698) | (0.0698) | (0.0894) | (0.0894) |
| Child6 | -0.0045 | -0.0024 | 0.0283 | 0.0285 |
| (0.0192) | (0.0192) | (0.0239) | (0.0239) |
| GFinc | 0.0276 \*\*\* | 0.0275 \*\*\* | 0.0051 | 0.0051 |
| (0.0061) | (0.0061) | (0.0051) | (0.0051) |
| HH\_Size | -0.0086 | -0.009 | -0.0174 \* | -0.0175 \* |
| (0.0088) | (0.0088) | (0.0088) | (0.0088) |
| HS | 0.0823 ^ | 0.0777 ^ | 0.1186 \*\* | 0.1178 \*\* |
| (0.0425) | (0.0425) | (0.0381) | (0.0381) |
| SomeCol | 0.1875 \*\*\* | 0.1835 \*\*\* | 0.2428 \*\*\* | 0.2415 \*\*\* |
| (0.0448) | (0.0448) | (0.0438) | (0.0438) |
| CollegeGrad | 0.1141 ^ | 0.1095 ^ | 0.1768 \*\* | 0.1776 \*\* |
| (0.0655) | (0.0655) | (0.068) | (0.068) |
| CollegePlus | -0.0932 | -0.1053 | 0.1232 | 0.125 |
| (0.0991) | (0.0992) | (0.1102) | (0.1103) |
| Score | 0.0049 \*\*\* | 0.0048 \*\*\* | 0.0038 \*\*\* | 0.0038 \*\*\* |
| (0.0007) | (0.0007) | (0.0006) | (0.0006) |
| Tenure | 0.0004 | 0.0004 | 0.0001 | 0.0001 |
| (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Experience | 0.0002 | 0.0002 | 0.0006 \*\*\* | 0.0006 \*\*\* |
| (0.0002) | (0.0002) | (0.0001) | (0.0001) |
| AvgHealth | 0.0024 | 0.0024 | -0.0127 | -0.0127 |
| (0.0292) | (0.0291) | (0.0297) | (0.0297) |
| PoorHealth | 0.0442 | 0.0423 | -0.0437 | -0.0434 |
| (0.043) | (0.043) | (0.046) | (0.0461) |
| NorthCentral | -0.0505 | -0.0514 | -0.1512 \*\*\* | -0.1509 \*\*\* |
| (0.0476) | (0.0475) | (0.0444) | (0.0444) |
| NorthEast | -0.1966 \*\*\* | -0.1963 \*\*\* | -0.2421 \*\*\* | -0.2424 \*\*\* |
| (0.0521) | (0.052) | (0.0489) | (0.0489) |
| South | -0.041 | -0.0416 | -0.1324 \*\* | -0.1322 \*\* |
| (0.0425) | (0.0425) | (0.0412) | (0.0412) |
| UnempRate | -0.0728 \*\*\* | -0.073 \*\*\* | -0.0806 \*\*\* | -0.0805 \*\*\* |
| (0.0096) | (0.0096) | (0.0091) | (0.0091) |
| SearchCount | -0.0629 \*\*\* | -0.0631 \*\*\* | -0.0508 \*\*\* | -0.0507 \*\*\* |
| (0.0069) | (0.0069) | (0.0065) | (0.0065) |
| Forced | 0.0122 | 0.023 | -0.4386 \*\* | -0.4314 \*\* |
| (0.1478) | (0.1478) | (0.1465) | (0.1466) |
| Ended | -0.1819 ^ | -0.1779 ^ | -0.2318 \*\* | -0.2305 \*\* |
| (0.0945) | (0.0944) | (0.0748) | (0.0748) |
| Illness | 0.1696 | 0.1619 | 0.1544 | 0.1533 |
| (0.4) | (0.3999) | (0.3876) | (0.3873) |
| Quit | -0.1442 ^ | -0.1406 | -0.112 | -0.111 |
| (0.0855) | (0.0854) | (0.0765) | (0.0765) |
| Union | 0.0574 | 0.0564 | -0.0032 | -0.0037 |
| (0.112) | (0.112) | (0.0829) | (0.0829) |
| Occupation Fixed Effects | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| Variable Coef. Std. Dev. | 0.3805 | 0.378 | 0.3786 | 0.378 |
| Significance Levels: ^=10%, \*=5%, \*\*=2.5%, \*\*\* 1%. Frailty modeled with Gaussian distribution and models estimated with *coxph* and *coxme* command in R. Standard errors in parathesis. Intercept SD indicates the standard deviation of the mixed effect constant terms estimated according to frailty across individual respondent (ID) and loglikelihood testing the significance of the random effects are all significant at the highest level. | | | | |

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. Using CPH also simplifies the inclusion of frailty in the likelihood estimation process. [↑](#footnote-ref-5)
6. See Gutierrez (2002) for details about parametric frailty survival models. We model the individual frailty or clustering using the Mixed Effect method included in the R package *coxme*. [↑](#footnote-ref-6)
7. 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 at the time of the interview, the interviewer is instructed to insert the interview date creating an error in coding an unemployment spell if the worker is employed at the time of the interview, complicates identifying spells that exist across calendar years, and there is no indicate if the respondent leaves 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. While the weight and height questions are asked in each survey, they are sometimes either missing or contain recording errors. [↑](#footnote-ref-9)
10. 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 and our estimates are robust to this removal. [↑](#footnote-ref-10)
11. The reference category is indicated with an asterisk. For the race category, individuals classified as “mixed” are removed and there is no Asian race category in the original data. [↑](#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. Gross family income is adjusted using the inverse hyperbolic sine transformation, which is comparable to using the natural log transformation but allows values equal to zero. [↑](#footnote-ref-13)
14. Reported in the initial interview. [↑](#footnote-ref-14)
15. 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-15)
16. 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-16)
17. Most of the respondents either do not report the reason for the start of the spell or there is missing data so the category UNKNOWN is used to capture these events. [↑](#footnote-ref-17)
18. After about 30 weeks the differences between the survival probability curves is hard to see in black and white. [↑](#footnote-ref-18)
19. While not shown, we utilize a loglikelihood test using the integrated log likelihood value to test the statistical significance of the individual specific effects and the null hypothesis of no frailty across individuals is rejected at the highest level. [↑](#footnote-ref-19)