Occupational Differences in BMI, BMI Trajectories, and Implications for Employment Status among Older U.S. Workers

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ABSTRACT

We examined associations between employment and obesity, arguing that risk for unhealthy weight may vary across occupational groups because they shape workplace exposures, social class standing, material resources, and norms and expectations about healthy behaviors and weight. We used a large sample of 51–61-year-old workers from the Health and Retirement study, tracking their body mass index (BMI) over time while accounting for potentially confounding influences of socioeconomic status and gender and exploring whether gender modified associations between occupational group, BMI, and retirement timing. Compared with women in professional occupations, women managers were less likely to be obese at baseline and were less likely to be in the obese upward trajectory class, while female professionals and operators and laborers were less likely than women in farm and precision production to be in the normal stable trajectory. Male professionals were less likely than men in sales, service, and operator and laborer positions to be obese at baseline and more often followed the normal upward trajectory than most other groups, though they and farm and precision production men were more likely to be in the overweight to obese trajectory than men in service occupations. Adjustment for sociodemographic and lifestyle characteristics reduced associations more for men than for women. While retirement risk differed across occupational groups, most of these differences were explained by socioeconomic, demographic, and lifestyle characteristics, especially for men. Obesity at baseline was an independent predictor of retirement but did not further explain differences in the timing of retirement by occupational group.

Increased longevity in many wealthy nations, combined with lower fertility rates, means that the old-age dependency ratio has risen substantially. However, older adults in countries like the United States (U.S.) are also living longer with potentially significant remaining work capacity (Weir, 2007), raising the possibility of an important demographic “windfall” of older adults who could stay productively employed for longer than in the past. Older workers respond strongly to pension incentives, and raising the age of eligibility for retirement pensions may yield benefits for financial solvency of nations; it could also improve the health of workers, to the extent that good jobs promote health, or at least do not harm it for most workers (Fisher, Ryan, & Sonnega, 2015). However, the rise in the fraction of the adult population that is overweight or obese could threaten this potential extension of working years into progressively later life. The prevalence of obesity among U.S. adults doubled between 1976–1980 and 1999–2000, increasing from 15.1% to 30.9% (Wang & Beydoun, 2007). A better understanding of the association between excessive body mass index (BMI) levels and the potential to remain productively employed is important for policy and intervention.

Importantly, the association between BMI and employment may run in both directions. High BMI could predict employment status and occupational conditions if it causes early labor market exit or limits occupational choice. At the same time, body weight may be affected by the varying experiences and expectations for workers in different broad occupational groups. Studies have found evidence for the hypothesized associations in both directions, but have some important limitations. Many have used cross-sectional data, making it difficult to establish the directionality of associations. Most studies have only measured BMI at a single point in time, but the trajectory of weight gain over time may also be critical for understanding whether a worker's occupational group is contributing to their risk of obesity, or if certain patterns of weight change are most strongly associated with labor market exit. Much of the strongest evidence based on prospective data has drawn on workers from wealthy European societies with very different social, employment, and policy environments than those that prevail in the United States, so those findings may not generalize to U.S. workers.

A further limitation is that many existing studies have focused on particular occupational groups, or do not represent older workers from across the U.S. Samples limited to a particular group or locale make it difficult to test a critical third association that could explain a link between BMI and either the specific occupation held or employment status more generally—confounding by gender or socioeconomic status (SES). Both gender and SES strongly influence occupational opportunity and choice, as well as influencing normative patterns of labor force attachment over the life course, and as discussed above, these may influence BMI trajectories. SES and gender also may influence typical life course trajectories of BMI, even net of occupation group or employment status. Without a large, representative sample of adults who vary on gender and SES, as well as in their occupations and labor force exit patterns, it is challenging to adequately assess the myriad ways that gender and SES may shape the composition of occupational and employment status groups and BMI groups.

To expand understanding of the associations between high BMI, occupation, and employment, while addressing these limitations of prior research, we conduct analyses to address several questions. First, we ask whether working in a particular occupational group is associated with the probability of being obese among U.S. workers nearing retirement age, and second, whether it is associated with their trajectories of BMI as they age. Third, we explore whether obesity at one point in time, or BMI trajectory over time, predict the timing of retirement, and whether either helps to explain any differences in the timing of retirement by occupational group. Fourth, we ask if the associations we find are robust to adjustment for SES, and fifth, whether they vary by gender. To address these novel questions, we use nationally representative data on a large sample of older adults from the Health and Retirement Study (HRS). The HRS sample represents men and women from across the SES spectrum and across the United States, capturing the full range of variation in occupations, retirement decisions, and BMI levels and trajectories of older Americans. HRS is a prospective study, allowing us to observe occupational group and BMI level among those employed at the start of the study, and to follow these workers as their BMI changes and as they retire. We consider focal associations while accounting for differences in SES with measures of educational attainment, household income, and wealth, and we stratify by gender and test for gender differences in associations. Given the relative scarcity of research addressing these questions in a large nationally representative sample, this study provides an important foundation for further explorations of the potential impact of occupation on body weight and of body weight on timing of retirement.

OCCUPATIONS AND OCCUPATIONAL GROUPS AS PREDICTORS OF BMI

Prior researchers have theorized about ways that occupation could influence levels of and changes in weight. Material and social resources, norms, experiences, and workplace conditions vary across broad occupational groups, such as white collar professionals or blue-collar operators and laborers, influencing their risk of obesity during later middle age, BMI trajectories over time, and their timing of retirement. While occupation was an even more defining social and material identity in earlier, industrializing periods of history, the values and practices associated with occupational groups are still socially relevant and may shape health lifestyles (Cockerham, 2005). Occupational groups are

comprised of people with similar work skills, but they also generate social networks based around workplace ties. These work networks and the behavioral and consumption expectations for workers who share them may shape health behaviors that influence BMI, including leisure time physical activity, dietary choices, other health behaviors, or preferences for body size. For example, a study of obesity prevalence by occupation in Washington State found that workers in protective services were about 2.5 times as likely to be obese as workers in health diagnosing occupations (Bonauto, Lu, & Fan, 2014), and that health behaviors including leisure-time physical activity explained some of the differences across these occupations. In that study, truck drivers and workers in transportation and material moving, and cleaning and building services also showed elevated rates of obesity that were partially explained by these behaviors (Bonauto et al., 2014). A study of U.S. adults in the National Health and Nutrition Examination Survey (NHANES) also found that it was important to account for activities outside the workplace when assessing BMI differences across occupational groups, because some white collar and service workers had low levels of physical activity at work, but high levels outside of work.

Figure 1 is a conceptual diagram that illustrates the associations implied by prior studies and our related research questions. Path Q1, marked by a heavy arrow running from occupational group to obesity, indicates our first research question of whether working in a particular occupational group is associated with the likelihood of being obese. Extant studies suggest this association, but most have not used nationally representative samples of U.S. workers, or have focused on specific occupations, but not broader occupational groups. Path Q2 indicates the second question, assessing whether occupational group is associated with trajectories of BMI (the wide arrow denotes measurement of BMI change over follow-up).

Relatively few studies have considered Q2, and few have moved beyond an assessment of change in BMI between two time points. To the authors' knowledge, none have considered whether occupational group predicts subsequent trajectories of BMI, but other studies have shown variation in the risk of high BMI by occupational prestige and social class (McLaren & Godley, 2009), measures that are associated with occupational group. We contribute by assessing long-term trajectories of BMI change, whether they are predicted by occupational group, and how they may themselves predict subsequent employment status change. Based on the existing evidence from cross-sectional data,

Figure 1. Conceptual diagram.

we expect that the association would operate over the career as exposures accumulate and behavioral differences across groups solidify as workers age. We expect that workers in occupational groups at the higher status end of the occupational ladder, such as white collar professionals and managers, will be less likely to be obese and will have more favorable trajectories of BMI change than those in lower status occupational groups, such as those in service occupations or blue collar occupations. We also expect occupational group differences to be at least partially explained by group differences in health lifestyle factors such as leisure time physical activity or health at baseline.

BMI AS A PREDICTOR OF EMPLOYMENT STATUS AND RETIREMENT

A separate body of research has considered how BMI may determine employment status itself. In [Figure 1](#), Q3 reflects our third research question of whether obesity at one point in time or BMI trajectory over time predicts the timing of retirement. Further, we assess whether baseline obesity or diverging BMI trajectories over time help to explain any differences in the timing of retirement by occupational group.

The influential job demands resources theory of occupational stress suggests that strain arises when the demands of work exceed the individual's resources for dealing with them ([Bakker & Demerouti, 2007](#)). More recently, this model has been applied in retirement research ([Fisher et al., 2015](#)). High BMI may cause individuals to doubt that they can meet the demands of the job, if adequate resources and accommodations are not available for heavier workers who may face mobility limitations or other disabilities. Additionally, obesity may be more likely to influence the retirement decision in occupations that are more physically demanding. That is, the demands of occupations that require a higher degree of physical mobility are likely to exceed the resources of workers carrying excessive body weight. On the other hand, occupations that involve sedentariness, a risk factor for the development of obesity, may allow heavier workers to remain at work longer even if they have mobility limitations. In this latter scenario, obesity itself does not necessarily lead to an imbalance between demands and resources.

Indeed, if they are not forced out because of an extreme imbalance between demands and resources, obese workers in less physically demanding jobs may need to stay on the job longer than they would prefer. This could occur if higher BMI is linked to increased health problems, requiring a worker to remain employed longer for financial or health insurance reasons, a situation labeled "job lock." Some occupational groups may be characterized by both high average worker BMI and fewer of the material assets needed to enable a financially viable retirement, such as adequate savings, a pension, and adequate provision for health care. These could include service occupations that are not physically demanding, but also do not offer the financial and other employment benefits of higher status white collar positions. In addition to these material realities, expectations about the appropriate timing of retirement may vary across broad occupational groups in ways that shape retirement timing ([Radl, 2013](#)).

Considerable empirical evidence supports expectations that higher BMI may be associated with an increased risk of exit from paid employment. [Robroek and colleagues \(2013\)](#) conducted a meta-analysis of the association between overweight and obesity, physical activity, and workforce departure through disability, unemployment, and early

retirement. Obese—and to a lesser extent, overweight—adults were more likely to leave work through disability pension, though they were not more likely to retire early ([Robroek et al., 2013](#)). A study of adults from the U.S. Panel Study of Income Dynamics (PSID) found that obesity was associated with a reduced likelihood of employment 13 years later ([Tunceli, Li, & Williams, 2006](#)), and a study using the HRS showed that for both men and women, a BMI of 35 or higher in 1992 increased the likelihood of early retirement by 2002 ([Renna & Thakur, 2010](#)). While past research has found that obese individuals retire earlier and are more likely to do so for health or disability reasons than their lower-BMI peers ([Renna & Thakur, 2010](#); [Roos et al., 2013](#)), further research is needed that considers older workers from across the United States, and considers not only point in time measures of BMI, but also trajectories of BMI. While we have found no studies of BMI trajectories as predictors of retirement, past theory, and evidence would suggest that trajectories of weight gain, especially those involving obesity, would predict earlier retirement. As such, differential BMI trajectories across occupational groups may help to explain occupational group differences in retirement timing.

SES AND GENDER AS PREDICTORS OF OCCUPATION, EMPLOYMENT STATUS, AND BMI

SES and gender are potentially complicating characteristics in our conceptual model of employment and BMI as workers near retirement, because they shape access to and progress in occupational career tracks ([Goldberg, Finkelstein, Perry, & Konrad, 2004](#)), the acceptability and timing of labor force exits ([Dahl, Nilsen, & Vaage, 2003](#)), and the shape of BMI trajectories over the life course ([Ailshire & House, 2011](#); [Krueger & Reither, 2015](#)). Accounting for these factors could thus mediate (in the case of SES and gender) or moderate (in the case of gender) associations between occupational group and BMI.

Some prior studies have explored SES and gender as explanations for BMI variation across occupations. Studies using samples from Washington State ([Bonauto et al., 2014](#)) and from the Netherlands ([Proper & Hildebrandt, 2010](#)) have shown that adjusting for SES and other factors substantially reduces differences in BMI across occupational groups. A study of working-aged Canadians showed that adjusting for education fully explained the association between occupational prestige and BMI for women, but explained less of the association for men, suggesting a larger independent influence of occupation for men ([McLaren & Godley, 2009](#)). The presence of these associations and variations are illustrated in Q4 in [Figure 1](#). Narrow arrows indicate that we expect that a role for education as a predictor of occupational group, obesity, BMI trajectory, and retirement, and expect that adjusting for other indicators of SES that are predicted by education (income, wealth, and access to pension) will weaken the link between occupational group and the timing of retirement.

Similarly, narrow arrows indicate that we expect gender to predict occupational group, obese status, BMI trajectory, and retirement timing, and that adjusting for it may reduce focal associations. However, gender may also modify some of the associations of interest. Dashed arrows paths for Q5 in [Figure 1](#) indicate that the connection between occupational group and obesity or BMI trajectory may vary for men and women, if they face different requirements or expectations even when they hold the same occupation. Moreover, the way that obesity or

BMI trajectory predicts retirement timing may vary by gender, if older men and women face different performance expectations at work or differentially experience stigma against early retirement. Some evidence suggests that gender influences the way BMI influences retirement timing. For example, [Houston, Cai, and Stevens \(2009\)](#) used data from the Atherosclerosis Risk in Communities (ARIC) study to assess the connection between weight at midlife (between ages 25 and 45–55) and the risk of retiring before age 65 at follow-up 9 years later, with models stratified by gender and race. After accounting for education, household income, health insurance status, occupation, occupational physical activity, marital status, and smoking, overweight and obesity were associated with and increased risk of earlier retirement in all groups except for white women. However, while [Houston and colleagues \(2009\)](#) assessed the role of weight at age 25 and at 45–55 years of age, they had to rely on retrospectively recalled weight at age 25, and they relied on measures from only two time points, limiting their ability to capture trajectories. Based on this limited extant evidence, we expect that obesity and BMI trajectories in later life will affect retirement timing for all workers, though the impact may differ for women and men.

METHOD

Data

The Health and Retirement Study (HRS) is a longitudinal biennial survey of adults in the United States with 12 waves of data now available. The first wave of data collection in 1992 included households with at least one adult between the ages of 51 and 61 years and, if that adult was partnered, their spouse or partner of any age. The baseline response rate for the HRS cohort is about 82%, and longitudinal response rates range from 85% to 90% ([Sonnega et al., 2014](#)). The original sample design included clustering and stratification as well as oversampling of Hispanics and African Americans. Sample weights adjust for these elements of sample design. HRS respondents who are unwilling or unable to complete an interview are offered the opportunity to have a proxy respondent, who is often a spouse or other relative, complete the interview. Researchers at the RAND Corporation produce a user-friendly version of the data ([Chien et al., 2015](#)). Twenty years (11 waves) of longitudinal data from the original HRS cohort (born 1931–1941) are currently available in the RAND version, used in this study.

The full sample for the 1992 HRS core interview includes 12,652 respondents. We used several criteria to obtain our analytic sample, first limiting the age range to those 51–61 years at baseline ($n = 9,546$), which removes age-ineligible spouse and partners. We next selected respondents with a non-zero sample weight ($n = 9,441$) and who were not proxy respondents ($n = 8,980$). A major criterion was to limit the sample to those who were “at risk” for retirement at baseline. To do this, we used the RAND labor force status variable, which includes the response options “full-time,” “part-time,” “unemployed,” “partly retired,” “retired,” “disabled,” and “not in the labor force.” We selected respondents who reported working full- or part-time, who were unemployed, or who were partly retired, yielding an analytic sample of 6,377. The “armed services” occupational category not included because it contained very few respondents and could not be appropriately merged with any other category, leaving 6,290 respondents. We selected respondents with complete information on key variables: presence of a pension ($n = 5,937$), BMI ($n = 5,905$), occupation ($n = 5,702$), and date of retirement, leaving a final analytic sample of 5,523.

Measures

Occupation group

Information collected in 1992 on current and longest held job was coded using the 3-digit 1980 U.S. Census Occupational Codes ([Nolte, Turf, & Servais, 2014](#)). To protect the confidentiality of respondents, the public release version of the occupation data provides 17 aggregated categories. The RAND version of HRS combines information on job history and occupations held to create two occupation variables: the occupation of the current job and the occupation of the longest-held job. We chose to use the ‘longest-held occupation’ as the main exposure variable. For those in all 17 occupational categories, the current job is also likely to be the longest-held job (between 70% and 90% of currently held jobs are also the longest held for these respondents).

To increase statistical power and generate more evenly sized occupational groups that still capture meaningful social variation in health lifestyle factors, we collapsed together some smaller groups from the 17 provided by RAND. We aggregated all five service categories (household, cleaning and building; protection; food preparation; health; and personal) into a single service occupations category. We aggregated all three operator categories together with farming, forestry, and fishing, and we also aggregated the mechanics and repairers, construction trades, and precision production occupational groups into a single category. Our final occupational group variable thus contained the following mutually exclusive categories, in rough order of their social status or prestige: (a) professional specialty and technicians and related support occupations (referred to in what follows as “professionals”), including codes 43–235 in the 1980 U.S. Census occupation coding scheme, (b) executive, administrative, managerial, and managerial-related occupations (“managers”), including occupation codes 3–37, (c) sales occupations (“sales”), including codes 243–285, (d) administrative support occupations, including clerical (“clerical”), including codes 303–389, (e) service occupations (“service”), including codes 403–469, (f) farm, forestry, and fishing and precision production, craft, and repair occupations (“farm and precision production,” including codes 473–699, and (g) operators, fabricators, and laborers (“operators and laborers”), including codes 703–889. We expect considerable variation in average education and gender composition across these broad occupational groups, as well as in their health lifestyle-related behaviors, all of which could lead to variation in BMI and timing of retirement.

Body mass index

At every wave, HRS respondents report their height and weight. These values were used to calculate BMI according to the standard formula (weight divided by the square of height—weight (kg)/[height (m)]²). We conduct analyses using two measures of BMI: a categorical measure of obesity at baseline and a trajectory measure that captures change in BMI over follow-up. A dichotomous measure of baseline obesity includes as obese the conventional Centers for Disease Control (CDC) groups of BMI 30–34.9 (class I obese), 35–39.9 (class II obese), and 40 or higher (class III obese). Following [Zheng, Tumin, and Qian \(2013\)](#), we used measures from 11 waves to create BMI trajectories with the SAS PROC TRAJ procedure, an add-on in SAS 9.4 ([SAS Institute Inc., 2015](#)). The trajectory procedure uses a multinomial mixture model that identifies clusters of trajectories of change, where repeated observations are available on the same respondents, and assumes an underlying mixture of population trajectories ([Jones & Nagin, 2007](#);

Jones, Nagin, & Roeder, 2001; Nagin, Lynam, Raudenbush, & Roeder, 1999). The trajectory procedure yielded six latent class trajectories of BMI over follow-up: normal stable; normal upward; overweight stable; overweight to obese; class I obese upward; and classes II/III obese upward. These results map closely to findings of other research using HRS (Zheng et al., 2013). To increase statistical power, we combined the last two trajectories to form a single category of obese (classes I, II, or III) with upward weight change (obese upward). We used the normal upward BMI trajectory as the referent category because it was one of the two most common in the sample and reflects a healthy pattern of weight change.

Retirement

HRS obtains detailed job history information at the baseline interview. In follow-up interviews, respondents who are not working for pay are asked when the job they reported holding at the previous interview ended. In this study, retirement was defined as the end date of the last held job.

Socioeconomic status

Education was measured in completed years as the main (early life) indicator of SES. Other aspects of SES included in analyses of retirement timing included household income, household wealth, and an indicator of holding a pension. The RAND income variable is the sum of all sources of household income including from wages, transfer payments, and investment income. The wealth measure is the sum of all sources of wealth (excluding secondary residences) minus all debt. Missing values for income and wealth are imputed according to procedures detailed in the RAND documentation (Chien et al., 2015). The income and wealth variables were divided by 10,000 for ease of interpretation. The RAND pension variable is a dichotomous indicator for presence of either a defined benefit (DB) or a defined contribution (DC) pension for the currently held job in 1992, with no pension as the referent category.

Demographic characteristics

Demographic predictors included age, race, marital status, and gender. We adjusted for age in years at baseline. Race was coded as “non-Hispanic white” and “other,” with “other” as the referent category. Marital status was coded as “married” or “not married” with “not married” serving as the referent. Female and male respondents were distinguished and all multivariable analyses were stratified by gender.

Health and health behaviors

HRS utilizes a standard measure of self-rated health, which asks respondents to rate their current health as “poor,” “fair,” “good,” “very good,” or “excellent.” Following common practice, we created a dichotomous variable for good health as “good,” “very good,” or “excellent,” with those reporting poor or fair health as the referent group. To indicate leisure-time physical activity, we used the RAND dichotomous indicator of participating in “vigorous physical activity or sports—such as heavy housework, aerobics, running, swimming, or bicycling” three or more times per week. RAND provides variables indicating current smoking and lifetime smoking. Using these, we created dichotomous indicators for “never smoked,” “current smoker,” and “former smoker.”

Analysis

Analyses were conducted using Stata SE 14 (StataCorp, 2015) (except for the trajectory procedure used to create the BMI trajectory measure as noted above). The 1992 respondent-level survey weight was applied to all analyses, and the complex sample design was addressed by using the `svy`—suite of commands in Stata. Descriptive statistics were generated for the analytic sample for all study variables. To demonstrate the heterogeneity in socioeconomic, demographic, and health characteristics across occupational groups, we present bivariate associations with age, race, gender, marital status, education, household income, household wealth, pension, self-rated health, leisure time physical activity, and smoking status.

To investigate the relationship between occupational group and obesity at baseline, we conducted a set of nested logistic regression models. Model 1 evaluated the risk of obesity in 1992 associated with occupational group and age. Model 2 added controls for education, race, and marital status, to adjust for SES and demographic characteristics, and for self-reported health, smoking, and leisure-time physical activity, to capture aspects of health lifestyles. These and all remaining multivariable analyses were stratified by gender. To evaluate the significance of potential gender differences in associations observed in the gender stratified models, we estimated a parallel set of logistic regression models for the pooled male and female sample, with all predictors interacted with gender (models not shown but available from authors). In the text below, we report on significant gender differences in odds, risk, or hazard ratios where relevant. To ensure that comparisons of coefficients across nested logistic regression models were not misleading, we re-estimated these models as linear probability models; results were unchanged, so we present logistic regression results for interpretability and consistency with the remainder of the analysis. In addition to presenting odds ratios for the stratified regression models, we also estimated predicted probabilities of obesity by occupational group, adjusting for all covariates in Model 2 (using mean values for all covariates in the predictions).

In the next set of analyses, we employed multinomial logistic regression to evaluate the association between occupational group and subsequent BMI trajectory class, comparing all other trajectories to the normal upward class. Challenges of interpretability when using multinomial logistic regression led us to focus on presentation and interpretation of predicted probabilities of being in each BMI trajectory category, adjusting for all covariates. We again evaluated the statistical significance of potential gender differences with fully gender interacted models, available on request, and comment on these in the text.

For the final stage of our analysis, we estimated Cox proportional hazards models to investigate the contribution of occupational groups and obesity at baseline or BMI trajectories over follow-up to the timing of retirement. We estimated four Cox regression models, each stratified by gender. We created the event variable (retirement) and a time to event variable based on the month and year of the last occupation observed. While HRS includes several work status variables, this is a good way to closely align the last occupation held with the date of workforce departure, which we define as retirement. Model 1 evaluated the associations of occupational category and age with the risk of retiring over an up to 20-year follow-up period. Model 2 further adjusted for education, race, marital status, self-reported health, smoking, leisure-time physical activity, household income, household

wealth, and whether the respondent had a pension, and also for either the categorical indicator of obesity at baseline or the BMI trajectory class. These models thus illustrate any association between occupational group or BMI (in the cross section or over follow-up) and timing of retirement, as well as showing whether BMI differences across occupational groups help to explain the association between occupational group and retirement timing.

RESULTS

Sample Description

Characteristics of the analytic sample are presented in Table 1. Among HRS respondents who were working for pay and between ages 51 and 61 in 1992, the occupational groups of professionals, managers, clerical and operators, and laborers each represented about 17% of the sample. Just over 9% reported a sales occupation, while service occupations and farm and precision production occupational groups each accounted for about 11% of the sample. At baseline, 21.3% of respondents were obese (i.e., BMI ≥ 30). We also display the CDC standard categories in Table 1 to illustrate that most of the respondents who fell into the dichotomous obese or not category were class I obese (BMI 30–34.9). Turning to the BMI trajectory classes, we observe that 31.3% of respondents followed a normal stable pattern over follow-up, with 26.0% following a normal upward trajectory of some weight gain. About 22% were stably in the overweight category over follow-up, while about 8.5% moved from overweight to obese and an additional 12% of respondents followed an obese upward trajectory. Over the follow-up period through 2012, 73.4% of the sample retired.

In the analytic sample overall, 48.3% were female and the average educational attainment was 12.8 years. The average age was 55.4 years and nearly 84% of respondents were non-Hispanic white. The mean annual household income was \$55,953, and mean household wealth was \$240,557. About 57% of the sample held a pension. Nearly 89% of the sample reported good, very good, or excellent overall health at baseline, and about 14% reported getting vigorous physical activity at least three times a week. Current smokers accounted for 24.7% of the sample, former smokers accounted for another 39%, and never smokers made up the remaining 36.3%.

Table 2 stratifies the analytic sample by occupational group to show differences in obesity at baseline, the likelihood of retirement occurrence, and sociodemographic and health lifestyle characteristics. The first row shows that the prevalence of obesity at baseline varied across occupational groups, ranging from 18.1% among those in managerial occupations to 26.4% among service workers. The likelihood of retirement over follow-up also varied, from a low of about 67% among those in the sales occupational group to a high of about 76% among those in clerical occupations. There was even more substantial variation across occupational groups in their gender composition, with women making up fully 83.3% of clerical workers but only 9.8% of farm and precision production workers. Professional and sales occupations included a relatively even balance of male and female workers, while managerial and operator and laborer occupational groups were majority male, and the service occupational group was majority female. Not surprisingly, there were also large differences in average educational attainment across occupational groups, with a high of 15.6 years among those in professional occupations and a low of 10.6 years among those in operator and laborer positions. Those in service and operator and laborer

Table 1. Descriptive Statistics of Study Variables

Variables	Mean	Percent	Standard Error
Occupational category			
Professionals		17.32	0.91
Managers		17.51	0.64
Sales		9.14	0.43
Clerical		16.70	0.55
Service		11.51	0.58
Farm and precision production		11.26	0.55
Operators and laborers		16.56	0.61
Obese (BMI ≥ 30)		21.34	0.71
CDC BMI category			
BMI < 18.5		0.90	0.15
18.5 $\leq$ BMI $\leq$ 24.9		35.37	0.88
25 $\leq$ BMI $\leq$ 29.9		42.38	0.73
30 $\leq$ BMI $\leq$ 34.9		16.06	0.56
35 $\leq$ BMI $\leq$ 39.9		3.75	0.27
BMI ≥ 40		1.53	0.16
BMI trajectory category			
Normal stable		31.28	0.62
Normal upward		25.98	0.66
Overweight stable		22.12	0.64
Overweight to obese		8.54	0.49
Obese upward		12.08	0.57
Retired over follow-up		73.43	0.70
Female		48.32	0.70
Education (years)	12.77		0.08
Age (years)	55.41		0.05
White		83.87	0.94
Married		76.09	0.73
Household income (\$)	55,953		1,357
Household wealth (\$)	240,557		10,596
DB or DC pension		56.66	0.81
Physically active		14.53	0.64
High self-rated health		88.79	0.56
Current smoker		24.70	0.86
Former smoker		39.00	0.88
Never smoked		36.30	0.85

Note. Analyses were weighted using the 1992 HRS respondent weight. The unweighted sample size is 5,523. BMI = body mass index; CDC = Center for Disease Control; DB = defined benefit; DC = defined contribution.

Source. Health and Retirement Study, 1992.

occupations had the lowest annual household incomes at about \$34–39,000, while professionals and managers reported much higher incomes, averaging about \$77–78,000. Health and health-related behaviors also varied across groups: the percentage of current smokers was about 30% in the sales, service, farm and precision production, and operator and laborer occupational groups, while it was only about 16% among those in professional occupations.

Table 3 shows the distribution of obesity and BMI trajectory classes across occupational groups by gender. While the overall gender difference in obesity, shown in the final row of the first two columns, is not striking, we find marked differences between men

Table 2. Distribution of Key Analytic Variables within Occupational Categories

	Professionals	Managers	Sales	Clerical	Service	Farm and Precision Production	Operators and Laborers
% Obese	19.95	18.12	21.06	19.92	26.41	19.95	25.22
% Retired over follow-up	73.05	71.76	67.05	76.16	73.62	75.23	74.84
% Female	54.87	34.75	51.09	83.33	73.09	9.82	27.95
Mean education (years)	15.59	14.02	12.74	12.68	11.1	11.51	10.63
Mean income (\$)	77,354	77,961	55,148	50,638	34,054	45,186	38,645
% Good health	94.25	94.28	90.00	90.20	83.06	86.78	80.54
% Physically active	20.15	19.93	11.70	10.18	12.31	12.54	11.80
% Current smoker	15.89	20.76	27.78	23.59	31.46	28.64	30.10

Note. Analyses were weighted using the 1992 HRS respondent weight. The unweighted sample size is 5,523.

Source. Health and Retirement Study, 1992.

and women in the professional, managerial, and farm and precision production occupational groups. About 23% of professional women were obese compared to only about 16% of professional men, while about 24% of women compared to 20% of men in farm and precision production occupations were obese. This gender difference is reversed for respondents in managerial occupations, with about 16% of female managers versus nearly 20% of male managers being obese. Interestingly, there were only modest gender differences in the prevalence of obesity for other occupational groups.

Turning to BMI trajectory classes in [Table 3](#), we find that overall, a higher proportion of men occupy the normal stable and overweight stable trajectories, while the proportions moving from overweight to obese and from obese upward are markedly higher for women. These overall patterns generally hold across occupational groups, with even greater gender differences appearing in some. The proportion of women professionals in the obese upward group is nearly twice that of men (14% and 8%, respectively) and the gender gap is even larger in the overweight to obese group (16% and 6%, respectively). While 35% of male managers are in the normal stable category (compared to about 28% of female managers), the gender difference is more marked in the overweight to obese group (14% of female managers and only 3% of male managers). Looking within trajectory groups and across occupational categories, two groups show a notable trend. More women in white collar occupational groups fall into the overweight to obese trajectory group, compared to their counterparts in service, farm, and other blue collar positions. Among men, we find the opposite pattern for the obese upward trajectory class, where blue collar and clerical workers are overrepresented relative to their white collar and service peers.

Is Occupational Group Associated with Obesity?

We turn now to multivariable analyses to further explore our research questions. We first assess whether occupational group is associated with obesity at baseline, after accounting for a variety of potential explanations for the association. Here and throughout the remainder of the analysis, we also address our fourth research question, which asks whether results are robust to adjustment for SES, by adjusting for educational attainment and other predictors. We also address our fifth question, assessing whether associations vary by gender, by stratifying all analyses and comparing results for men and women.

[Table 4](#) presents odds ratios, with 95% confidence intervals (CI) in parentheses, from logistic regression models predicting obesity at baseline. The first column for each model presents results from the model estimated for women, while the second in each pair presents the results from the model estimated for men.

After adjusting only for age in Model 1, we find that women in managerial occupations have a significantly lower risk of obesity than women in professional occupations (the reference category), with an odds ratio of 0.61 (CI = 0.41–0.90). Among men, we find that those in sales (OR = 1.62), service (OR = 1.85), and operator and laborer occupations (OR = 1.75) have a higher risk of obesity than professionals. We assessed whether these and all gender differences in results were statistically significant by referring to a model estimated on the pooled male and female sample that incorporated interaction terms with all covariates and gender (results not shown). Results from the fully interacted model confirm that the lower risk of obesity among managers than among professionals for women—but not men—is a significant, gendered difference. Similarly, the higher risks among those in sales or operator and labor occupations relative to professionals that we observe for men only are significant or marginally significant gendered differences, respectively. Older individuals were at lower risk of obesity (a finding that is significant in the male model only but for which the pooled model finds no significant gender difference).

In Model 2, we adjusted for education, our key measure of SES that could plausibly predict both occupation group and BMI in later life. We also adjusted for race and marital status, other important sociodemographic predictors of BMI, and self-reported health, smoking status, and leisure-time physical activity, all health lifestyle factors that vary across occupational groups and could explain occupational differences in obesity observed in Model 1. Some of these factors were significant predictors of obesity, but we found that adjustment for them did not dramatically change occupational group differences for women, with those in managerial occupations remaining at significantly lower risk than professionals. After adjusting for these factors among men, however, the occupational group differences found in Model 1 weaken considerably. Those in sales were no longer at significantly greater risk than professional men, while those in service or operator and laborer occupations now had only marginally greater risk. In these fully adjusted models, the lower risk of obesity among managers than among professionals for women, but not men, remained a

Table 3. Obesity and BMI Trajectory Category by Occupational Group and Gender

	Obese		Normal Stable		Normal Upward		Overweight Stable		Overweight to Obese		Obese Upward	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Professionals	23.33	15.84	24.39	33.16	27.54	33.16	17.98	20.32	15.65	5.82	14.44	7.75
Managers	15.57	19.48	27.69	35.26	30.63	35.26	18.70	24.20	14.21	3.02	8.77	8.72
Sales	19.12	23.09	26.67	34.15	28.40	34.15	19.78	27.87	12.58	3.32	12.58	10.64
Clerical	20.00	19.45	27.21	36.36	27.32	36.36	18.24	29.88	14.25	3.39	12.98	8.98
Service	26.60	25.88	29.28	37.09	22.19	37.09	24.00	21.45	9.20	2.88	15.33	14.92
Farm and precision production	23.91	19.51	41.51	37.24	19.57	37.24	15.11	23.97	8.68	5.55	15.12	11.60
Operators and laborers	26.80	24.61	25.28	34.00	28.69	34.00	21.42	26.01	8.54	5.55	16.07	13.50
Total	21.90	20.82	21.17	35.13	26.94	25.07	19.63	24.45	12.80	4.56	13.45	10.79

Note. Analyses were weighted using the 1992 HRS respondent weight. The unweighted sample size is 5,523.

Source. Health and Retirement Study, 1992.

significant gendered difference, as did the higher risk among those in sales or operator and laborer occupations, relative to professionals, that we observe for men only.

Model 2 also shows that consistent with past research and expectations, white race and married status predicted significantly lower risk of obesity among women only, while good health, being a current smoker (relative to never smoking) and leisure-time physical activity predicted significantly lower risk for men and women. More years of education are associated with a marginally significantly lower risk of obesity among women only, but the pooled model with interaction terms finds no significant gender difference in the protective effect of education.

To illustrate differences across occupational groups and the impact of adjusting for potential confounders and explanatory factors, Figure 2 plots the predicted probabilities of obesity at baseline, based on the results of Model 2 in Table 4, and after setting values for all predictors at their gender-specific means. Results for women in the upper panel of Figure 2 show that those working in managerial occupations still have a lower risk of obesity than professional women or those in service occupations, even after we assign all women the same values of age, education, race, marital status, self-rated health, smoking, and physical activity. The lower panel in Figure 2 shows that there were no longer statistically significant differences across occupational groups in the likelihood of being obese after these adjustments, even though levels of obesity varied somewhat across groups, as they did for women. In sum, the results shown in Table 4 and Figure 2 suggest that there is occupational group variation in obesity among workers approaching retirement age. We find a greater number of significant differences among men, and also are better able to explain them among men when we address educational differences and variation in health lifestyle behaviors across occupational groups.

Is Occupational Group Associated with BMI Trajectory?

We now assess whether occupational group at baseline is associated with subsequent trajectory of BMI, after adjustment for a range of factors. Results obtained from multinomial logistic regression models are presented in Appendix A as risk ratios and 95% confidence intervals, with results for women shown in the upper panel and for men in the lower panel. The first column for each trajectory class shows results for the occupational groups adjusting only for age, while the second column shows results additionally adjusted for years of education, race, marital status, self-rated health, smoking status, and leisure-time physical activity. Risk ratios shown in Table 5 refer to the relative likelihood of being in a particular trajectory class, compared to being in the normal upward class, comparing a given occupational group to professionals. These results are complex to interpret when reading directly from the regression table, so we turn to predicted probabilities to discuss our findings.

Figure 3 presents predicted probabilities of being in each of the five BMI trajectory classes, based on the results of Model 2 in Appendix A, and after setting values for all predictors at their gender-specific means. Results for women in the upper panel of Figure 3 show that those working in managerial occupations at baseline have a lower likelihood of following the obese upward trajectory than women in professional occupations, even after we assign all women the same values of age, education, race, marital status, self-rated health, smoking, and physical activity. Additionally, professional women and those in operator and laborer occupations are significantly less likely than those in farm and precision

Table 4. Odds Ratios from Nested Logistic Regression Models of Baseline Obesity, Stratified by Gender

	Model 1		Model 2	
	Women	Men	Women	Men
Professionals	1.00 (—)	1.00 (—)	1.00 (—)	1.00 (—)
Managers	0.61* (0.41–0.90)	1.29 (0.90–1.85)	0.58* (0.38–0.88)	1.24 (0.85–1.81)
Sales	0.78 (0.50–1.20)	1.62* (1.04–2.53)	0.69 (0.40–1.16)	1.48 (0.93–2.35)
Clerical	0.82 (0.62–1.10)	1.30 (0.73–2.31)	0.74 (0.51–1.06)	1.13 (0.61–2.11)
Service	1.19 (0.84–1.70)	1.85* (1.15–2.99)	0.86 (0.54–1.34)	1.64+ (0.97–2.77)
Farm and precision production	1.04 (0.51–2.12)	1.29 (0.86–1.94)	0.78 (0.35–1.75)	1.10 (0.71–1.72)
Operators and laborers	1.21 (0.87–1.69)	1.75** (1.23–2.50)	0.82 (0.49–1.36)	1.43+ (0.95–2.16)
Age	0.99 (0.95–1.02)	0.97* (0.94–1.00)	0.97 (0.94–1.01)	0.96** (0.93–0.99)
Years of education			0.90+ (0.91–1.01)	0.98 (0.94–1.02)
White race			0.69** (0.54–0.88)	1.02 (0.81–1.28)
Married			0.69** (0.56–0.84)	1.31 (0.89–1.94)
Good health			0.49** (0.38–0.63)	0.49*** (0.37–0.66)
Former smoker			1.17 (0.93–1.48)	0.97 (0.81–1.17)
Current smoker			0.61** (0.47–0.80)	0.61*** (0.48–0.79)
Physically active			0.60* (0.40–0.91)	0.59** (0.43–0.81)

Note. Analyses were weighted using the 1992 HRS respondent weight. The unweighted sample size is 5,523.

Source. Health and Retirement Study, 1992.

Significance level: + $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

production occupations to be in the normal downward class. Turning to the lower panel of Figure 3, we find that even after adjustment for all predictors, men in sales, clerical, farm and precision production, and operator and laborer occupations are less likely than professional men to be in the normal upward trajectory class, while professionals and those in farm and precision production occupations are more likely than those in service occupations to belong to the overweight to obese trajectory class. These results for BMI trajectory classes, like those for baseline obesity, suggest differences across occupational groups that are more extensive for men than for women, and even after adjustment for SES, sociodemographic characteristics, and health lifestyle behaviors.

Does Obesity or BMI Trajectory Predict the Timing of Retirement? Does Either Account for Differences in Retirement Timing Across Occupational Groups?

We turn now to our third research question, asking whether obesity at baseline or BMI trajectory over follow up predict retirement timing, whether either helps to explain any differences retirement timing

across occupational groups, and whether any associations persist after adjusting for other factors known to predict retirement. Table 5 presents results from Cox proportional hazard models predicting retirement over follow-up, with results for women in the left column of each pair, and for men in the right column. We first consider whether there are occupational differences in retirement timing, then adjust for covariates, and finally introduce measures of BMI as potential mediating factors that could explain associations between occupational group at baseline and retirement timing.

The first two columns of Table 5 show the relative risk of retiring over the 1992–2012 follow-up period among respondents in each occupational group, relative to those in professional occupations, adjusting only for age. Before adjusting for any measures of BMI or other predictors of retirement, women in managerial and sales professions were likely to work longer relative to women working in professional occupations (i.e., the risk of retiring is significantly lower). Those in clerical and service occupations also showed marginally lower risk of retiring than professional women. Turning to the results for the

Figure 2. Predicted probabilities of obesity for men and women by occupational group, after adjustment for all predictors and setting all predictors at gender-specific means.

male-specific model, we find that those working in clerical, farm and precision production, or operator and laborer occupations worked significantly longer than professionals. Age was also a significant predictor of retirement for both men and women.

Importantly however, pooled models that include interactions with gender for all predictors (not shown) suggest that the hazards of retirement in managerial, sales, and farm and precision production occupations do not differ significantly by gender, despite the significance levels shown in Table 5 for the gender-specific models. We conclude that the discrepancy arises because the magnitudes of the gender gaps and the hazard ratios associated with these occupational groups, as compared to professionals, are not very large. By contrast, pooled models do support significant differences in the magnitude and direction of the gender gap between workers in clerical, service, and operator and laborer occupations and their respective professional counterparts. Taking the results from the pooled models into account, then, we conclude that managerial and sales workers of both genders may retire slightly later than professionals, while farm and precision production workers may retire somewhat earlier. Where men and women diverge is among clerical workers and service workers; groups in which only women retire later than their professional counterparts, and among operators and laborers, among whom only men appear to retire earlier than their professional counterparts.

After adjusting for an array of predictors in Model 2, but not yet introducing measures of BMI, we find little change in the relative hazards of retirement across occupational groups among women, though the marginally significant difference between service and professional women has now been eliminated. There is more substantial change in the results for men, among whom there are no longer any significant

differences across occupational groups. Results from the pooled and fully interacted models with these same adjustments (not shown) now show no significant gender differences in the relative hazards associated with any occupational groups. Taken together, these results from the stratified and pooled models suggest that even after adjustment for a wide array of potential predictors and mediators of the association between occupational group and retirement, managerial and sales workers of both genders may remain slightly less likely to retire than professionals, and that the gender difference in the relative risk of retiring among clerical workers may still diverge (lower for women, not different for men, relative to their professional counterparts).

In Model 3, we adjust further for an indicator of obesity at baseline to see whether it is associated with retirement net of these occupational groups and controls, and also whether it accounts for any of the remaining occupational group variation in retirement timing. Gender-stratified results in Table 5 show that while obesity is significantly positively related to the risk of retiring among men, its inclusion does not meaningfully change results for other predictors, including occupational group. Moreover, results from the pooled and fully interacted model yielded no gender difference in the influence of obesity, suggesting that both men and women may retire slightly earlier if they are obese. Results for Model 4 show no independent impact of BMI trajectory class on the likelihood of retirement for men or women, and that including the measure does not change the results from Model 2. Overall, these results suggest that retirement timing varies across broad occupational groups, with some gender differences in the way occupational groups vary. Adjusting for SES and sociodemographic predictors does more to account for these differences among men than women, and while obesity at baseline predicts earlier retirement, it does not help to further explain occupation group differences in retirement timing for men or women.

DISCUSSION

Researchers have become increasingly interested in the connection between employment and body weight across adulthood. Our study is novel because we assess the way occupations shape obesity risk, as well as the way that body weight influences the risk of leaving employment, together in the same analysis. We first asked whether occupational group and obesity were associated at the baseline interview, when HRS respondents were 51–61 years of age, and then considered a more novel question with prospective data, asking whether occupational group predicted subsequent BMI trajectory over follow-up. Our third research question turned to whether baseline obesity or BMI trajectory predicted retirement timing, and whether they helped to explain any occupation group variation in the timing of retirement. We were further able to add to the literature by using a nationally representative sample that covered women and men from across the social spectrum, and considering a fourth question of whether differences in socioeconomic resources accounted for the associations we found, and a fifth question of whether any of our findings differed by gender.

In answer to our first question, we found that compared with women in professional occupations, women managers were significantly less likely to be obese. Results differed for men, among whom those in sales, service and operator and laborer positions were more likely than professional men to be obese. There are few ready comparisons for our findings, because other studies have

Table 5. Hazard Ratios for Cox Regression Models of Retirement, Stratified by Gender

	Model 1		Model 2		Model 3		Model 4	
	Women	Men	Women	Men	Women	Men	Women	Men
Professional	1.00 (—)	1.00 (—)	1.00 (—)	1.00 (—)	1.00 (—)	1.00 (—)	1.00 (—)	1.00 (—)
Managerial	0.85* (0.41–0.99)	0.97 (0.82–1.15)	0.84* (0.72–0.99)	0.95 (0.79–1.15)	0.85* (0.72–1.00)	0.95 (0.79–1.14)	0.85* (0.72–1.00)	0.95 (0.79–1.15)
Sales	0.78* (0.63–0.96)	0.94 (0.76–1.15)	0.79* (0.64–0.97)	0.91 (0.73–1.13)	0.79* (0.64–0.97)	0.90 (0.72–1.12)	0.79* (0.64–0.97)	0.90 (0.72–1.13)
Clerical	0.87+ (0.78–1.01)	1.41** (1.10–1.80)	0.86+ (0.74–1.01)	1.17 (0.90–1.53)	0.87+ (0.74–1.01)	1.16 (0.89–1.53)	0.87+ (0.74–1.01)	1.16 (0.89–1.52)
Service	0.87+ (0.75–1.05)	1.14 (0.87–1.51)	0.89 (0.75–1.06)	1.02 (0.74–1.41)	0.90 (0.75–1.06)	1.01 (0.74–1.39)	0.90 (0.76–1.06)	1.02 (0.74–1.41)
Farm and precision production	1.05 (0.79–1.40)	1.26** (1.07–1.48)	1.05 (0.78–1.43)	1.11 (0.90–1.36)	1.06 (0.78–1.44)	1.11 (0.90–1.36)	1.06 (0.79–1.44)	1.10 (0.90–1.36)
Operators and laborers	0.92 (0.75–1.14)	1.28** (1.07–1.52)	0.89 (0.71–1.13)	1.13 (0.92–1.38)	0.89 (0.71–1.13)	1.12 (0.91–1.37)	0.89 (0.71–1.13)	1.12 (0.92–1.38)
Age	1.08*** (0.95–1.02)	1.05*** (1.04–1.07)	1.09*** (1.07–1.11)	1.06*** (1.00–1.08)	1.09*** (1.07–1.11)	1.06*** (1.04–1.08)	1.09*** (1.07–1.11)	1.06*** (1.04–1.08)
Education			0.99 (0.97–1.01)	0.98* (0.96–1.00)	0.99 (0.97–1.01)	(0.98)* (0.96–0.99)	0.99 (0.97–1.01)	0.98+ (0.96–1.01)
White race			1.05 (0.93–1.18)	1.18** (1.04–1.34)	1.05 (0.93–1.19)	1.18* (1.04–1.34)	1.06 (0.94–1.20)	1.19** (1.05–1.34)
Married			1.09 (0.98–1.21)	0.86* (0.75–0.99)	1.09+ (0.98–1.21)	0.86* (0.75–0.98)	1.10+ (0.99–1.21)	0.86 (0.75–0.98)
Good health			0.807* (0.67–0.97)	0.89 (0.75–1.05)	0.81* (0.68–0.98)	0.90 (0.76–1.06)	0.83* (0.69–0.99)	0.90 (0.75–1.06)
Former smoker			1.11* (1.00–1.24)	1.14* (1.00–1.30)	1.11* (1.00–1.23)	(1.15)* (1.01–1.30)	1.11+ (0.99–1.23)	1.14* (1.00–1.30)
Current smoker			1.22** (1.07–1.39)	1.33*** (1.16–1.53)	1.22** (1.08–1.39)	1.35*** (1.17–1.54)	1.24** (1.09–1.41)	1.34*** (1.16–1.55)
Physically active			0.92 (0.79–1.08)	0.94 (0.82–1.07)	0.93 (0.79–1.09)	0.95 (0.83–1.08)	0.94 (0.81–1.10)	0.94 (0.82–1.08)
Household income			1.02** (1.01–1.03)	0.99 (0.99–1.01)	1.02** (1.01–1.03)	1.00 (0.99–1.01)	1.02** (1.01–1.03)	1.00 (0.99–1.01)
Household wealth			1.00 (0.99–1.00)	1.00* (0.99–1.00)	1.00 (0.99–1.00)	0.99* (0.99–1.00)	1.00 (0.99–1.00)	0.99 (0.99–1.00)
Holds a pension			1.25*** (1.11–1.42)	1.44*** (1.31–1.58)	1.25*** (1.11–1.42)	1.44*** (1.31–1.59)	1.25*** (1.11–1.42)	1.44*** (1.31–1.58)
Obesity								
BMI <30					1.00 (—)	1.00 (—)		
BMI >f30					1.06 (0.94–1.20)	1.13* (1.01–1.26)		
BMI trajectory								
Normal stable							1.04 (0.92–1.17)	1.10 (0.96–1.27)
Normal upward							1.00 (--)	1.00 (--)
Overweight stable							1.07 (0.93–1.24)	1.11 (0.98–1.25)
Overweight to obese							0.98 (0.82–1.17)	1.17 (0.88–1.56)
Obese upward							1.17+ (0.99–1.39)	1.15 (0.96–1.38)

Note. Analyses were weighted using the 1992 HRS respondent weight. The unweighted sample size is 5,523.

Source. Health and Retirement Study, 1992.

Significance level: + $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Figure 3. Predicted BMI trajectory class values for men and women by occupational group, after adjustment for all predictors and setting all predictors at gender-specific means. **Figure 3** shows the difference in predicted proportion of respondents in an occupational group in each BMI trajectory class, after adjusting for all covariates in Model 2, Appendix A, and indicates comparisons that are significantly different from those in other occupational groups. Among women, those in the professional or operations/laborer occupations were less likely to be in the normal-downward BMI trajectory than farm and precision production workers, while managers were less likely than professional women to be in the obese-upward trajectory class. Men in sales, clerical, farm and precision production, and operator and laborer occupations are less likely than professional men to be in the normal upward trajectory class, while professionals and those in farm and precision production occupations are more likely than those in service occupations to belong to the overweight to obese trajectory class.

operationalized occupational status in different ways. However, a study of employed adults in Washington State that considered more detailed occupational titles found that workers in protective service occupations and cleaning and building services, as well as truck drivers and those in transportation and material moving, were considerably more likely to be obese when compared to those in health-diagnosing occupations (Bonauto et al., 2014). While they were not stratified by gender, the findings Washington State adults are reasonably consistent with ours for men, given that they found a higher risk for some groups of service workers and for operators than for a specific class of professionals.

Regarding our fourth research question, we found also that after accounting for SES, sociodemographic characteristics and aspects of health lifestyles that varied across occupational groups, the obesity gap between managers and professional women was unchanged, but differences by occupational group had weakened for men and were no longer significant (or only marginally so). Bonauto and colleagues (2014) found that for adults in Washington State, health lifestyle factors like leisure-time physical activity helped to explain the difference in obesity risk across occupational groups, but they did not stratify their analyses by gender. In contrast to our findings, a study of working-aged Canadians found that adjusting for education fully explained the association between occupational prestige and BMI for women, but explained less of the association for men (McLaren & Godley, 2009), but differences may be due to our measurement of occupational groups instead of occupational prestige, since the two indicators capture different aspects of status, resources, and expectations.

In answer to our second research question, we found differences by occupational group in trajectories of BMI over follow-up that again varied by gender. Even after we gave all respondents the same sex-specific mean values on all predictors, predictions from our models showed that female managers were less likely than professionals to be in the obese upward trajectory class, while female professionals and operators and laborers were less likely than their farm and precision production counterparts to be in the normal stable trajectory class. Among men, predicted probabilities revealed that professionals had a greater likelihood of being in the most favorable normal upward trajectory class than those in sales, clerical, farm and precision production, or operator and laborer occupations. Male professionals and farm and precision production workers were, however, more likely to be in the overweight to obese trajectory than their counterparts in service occupations. To our knowledge, there are no prior studies with which to compare these findings, since nearly all prior studies lacked prospective data needed to construct trajectories of body weight change.

The resilient differences between professionals and others in risk of obesity and risky BMI trajectories, even after we adjust for possible confounders and some key lifestyle risk behaviors, deserve further consideration. Future studies should use larger samples to consider more detailed occupations and identify which are driving the variation across broader occupational groups; the use of these broad groups is probably generating conservative estimate due to within-group heterogeneity. Studies should also consider the importance of differences across occupations and occupation groups in the average level of exposure to workplace conditions that matter for weight gain (Pandalai, Schulte, & Miller, 2013). Exposures known to be important for BMI and that may vary considerably both across and within occupational groups are physical activity on the job (Steeves et al., 2015), sedentarity (Choi et al., 2010; Wilmot et al., 2012), aspects of work schedules, such as shift work (Schulte et al., 2007), long work hours and working overtime, and the psychosocial stress of the job. These exposures can be linked to weight gain via mechanisms including limited physical activity, inadequate sleep, or unhealthy coping behaviors, such as comfort eating (Solovieva, Lallukka, Virtanen, & Viikari-Juntura, 2013). Ideally, future studies also will use robust measures of a wide range of workplace conditions to examine whether they account for the occupational group differences that remain. In analyses not shown but available on request, we explored the potential explanatory role of self-reported working conditions at baseline among those whose job at

baseline was their main career job, including a physical activity on the job, work hours (<40, 40–54, 55+), and stressfulness of the job. While a few of these predicted obesity or BMI trajectory net of other factors, their inclusion did not account for gaps across occupation groups reported above, but many other factors could be considered.

Future research could also measure and model change in working conditions over time. Change in specific exposures at work, such as in physical activity or sedentariness, have been linked to within-person changes in body weight. For example, [Monda and colleagues \(2007\)](#) found that among 18–55-year-old Chinese adults, increases in occupational physical activity were associated with lowered body weight for both men and women, while a study of 5-year changes in occupational sitting time, a key indicator of sedentary work, were associated with changes in BMI among women in a Danish occupational cohort of adults 18–59 at baseline ([Eriksen et al., 2015](#)). It is possible that working conditions are changing at different rates across occupations and occupational groups, leading to divergence in the way BMI is changing for different groups of workers as they age. Modeling the intricate potential feedback associations between changes in working conditions and changes in body weight will be complex but potentially could provide important advances on the existing evidence.

Our third research question asked whether obesity at one point in time or BMI trajectory over time predicts the timing of retirement, and whether they help to explain any differences in the timing of retirement by occupational group. While there were some differences across occupational groups, these were largely explained by SES and sociodemographic characteristics of incumbents, particularly for men. Once we adjusted for these differences, obesity at baseline slightly increased the hazard of retirement, but did not further explain remaining occupational group differences. BMI trajectory class over follow-up was not significantly associated with retirement risk, and including this measure did not account for any remaining occupational group differences. In a robustness check not shown here, we estimated models of retirement timing with obesity or BMI trajectory as the sole predictor, but our substantive conclusions did not differ. These findings are somewhat surprising given one study of U.S. adults that found overweight and obesity to predict early retirement in most race–gender groups ([Houston et al., 2009](#)). However, that study was focused on early retirement, included a younger group of workers and studied the impact of BMI between respondents' mid-twenties and mid-forties, a very different design than ours, and one that might include some high-BMI individuals who had already left the labor force before the HRS would start interviewing them in their fifties. Future research could assess whether different ways of measuring BMI trajectories might yield more powerful prediction or mediation in retirement models, or if the association is more evident in younger cohorts.

Our results across multiple descriptive and multivariable analyses provided insight on our fourth and fifth research questions. Especially for men, adjustment for SES and other factors accounted for a considerable amount of the association between occupational group and obesity or BMI trajectory, and also accounted for more of the link between occupational group and timing of retirement. Moreover, gaps across occupational groups in obesity or BMI trajectory differed for men and women, and the predictors used here were more effective in explaining differences among men than those among women. These gender differences are fertile territory for future studies.

Like every study, this one has important limitations. One possible concern is selective mortality; the HRS is a large, diverse sample that represents the occupational spectrum of U.S. workers and allows us to assess potential confounding by SES and moderation by gender. However, HRS begins collecting data from those who are 51 or older at baseline, and it is possible those with very risky BMI profiles were not interviewed or were not still employed at baseline, and were not in our analytic sample. Sample weights address selection to some degree, but studies using prospective data collected from earlier ages would be valuable. Moreover, respondents passed away over follow-up and were omitted from our analyses for analyses requiring longitudinal follow-up measures. In a robustness check not shown here but available upon request, we re-estimated the predictors of retirement using models with death over follow-up as a competing risk, but results were very similar to those shown here. This is not surprising when considering that only about 5% of these middle-aged, employed respondents died over follow-up. Competing risks are more likely to bias results when they are closer in prevalence to the outcome of interest ([Gondara, 2015](#)). Additionally, a substantial fraction of the sample was still employed at the end of follow-up. Given that retirement eventually occurs for nearly all individuals at older ages, and that the retirement event has been linked to obesity, analyses could be extended to future HRS waves to see whether these findings change as more adults retire. Finally, future studies should consider whether these findings apply to younger cohorts. The prevalence of obesity is rising over time, and individuals are spending a longer fraction of the life course with high BMI, so its potential mediational role in the relationship between occupations and retirement may change as the demands of occupations and the characteristics of workers in those occupations also change. Future work could also assess whether and how obesity and mediating factors such as wages are associated, potentially reciprocally, with BMI change over time as women and men age ([Cawley, 2000](#)). As BMI levels have risen, their impact on opportunities in the workplace, and the accommodations made available, may also be changing.

Future research in this area should also consider using a variety of measures of body mass and fatness, rather than relying solely on measures of BMI, which have been found to misclassify some persons as obese or nonobese, and is less accurate for men than for women ([Burkhauser & Cawley, 2008](#)). Additionally, waist circumference has been identified as a potential improvement over or important additional measure when using BMI among older persons, as waist circumference rises persistently as people age, while their BMI rises less persistently as they lose muscle mass ([Vlassopoulos, Combet, & Lean, 2014](#)). As follow-up of HRS continues, a measure of waist circumference will be available, but at present there was not sufficient follow-up after this new measurement started to be collected to study long-term outcomes of occupational group membership. Finally, future work should consider not only how gender may predict occupational group and BMI, as well as retirement timing and the associations between all of these, but also how intersectional identities of gender, race, and SES matter for older workers, with some studies suggesting further complexities ([Ailshire & House, 2011](#)) that were beyond the scope of this analysis to explore.

Despite some limitations, these findings offer new insights into the associations among occupational group, risky body weight profiles and retirement timing. They suggest that interventions to reduce inequalities in self-rated health and behaviors like leisure-time physical activity will

lessen the obesity gaps between occupational groups for men more than for women. The weak associations we find between obesity or BMI trajectory and retirement timing suggest, however, that interventions to change weight may not have an overwhelming influence on retirement timing among those still working into their fifties and leaving work around the normal retirement age. Most adults spend a great deal of their time in paid employment throughout midlife and into their older years, so to the extent that their work lives influence behaviors and exposures relevant for unhealthy BMI, occupations matter. However, subject to verification and extension in future research as outlined above, our results suggest the importance not only of occupation-specific drivers of body mass and retirement, but also the fundamental influence of SES and gender, which influence the workplaces where older adults find themselves, their health relevant behaviors throughout life that shape later life BMI, and their decisions about retirement.

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APPENDIX A. ODDS RATIOS FROM MULTINOMIAL LOGISTIC REGRESSION MODELS OF BMI TRAJECTORIES, STRATIFIED BY GENDER

	Normal Stable		Overweight Stable		Overweight to Obese		Obese Upward	
	Age Only	Adjusted	Age Only	Adjusted	Age Only	Adjusted	Age Only	Adjusted
Women								
Managers	1.02 (0.73–1.44)	1.01 (0.71–1.44)	0.94 (0.55–1.59)	0.92 (0.50–1.67)	0.82 (0.49–1.36)	0.85 (0.49–1.47)	0.55* (0.31–0.96)	0.53** (0.29–0.96)
Sales	1.07 (0.61–1.86)	1.03 (0.56–1.90)	1.07 (0.61–1.90)	1.01 (0.50–2.04)	0.78 (0.47–1.30)	0.83 (0.45–1.55)	0.86 (0.48–1.53)	0.74 (0.39–1.43)
Clerical	1.13 (0.82–1.54)	1.08 (0.75–1.54)	1.02 (0.66–1.58)	0.96 (0.56–1.65)	0.92 (0.55–1.54)	1.03 (0.53–1.98)	0.91 (0.59–1.40)	0.81 (0.48–1.36)
Service	1.49* (1.05–2.12)	1.28 (0.81–2.00)	1.66* (1.02–2.70)	1.32 (0.71–2.47)	0.73 (0.41–1.31)	0.80 (0.43–1.49)	1.33 (0.84–2.12)	0.91 (0.50–1.63)
Farm and precision production	1.00 (0.66–1.52)	0.83 (0.51–1.35)	1.15 (0.71–1.88)	0.86 (0.45–1.68)	0.52* (0.29–0.95)	0.59 (0.28–1.27)	1.09 (0.67–1.78)	0.68 (0.34–1.33)
Operators and laborers	2.41* (1.05–5.57)	2.10 (0.86–5.12)	1.19 (0.39–3.68)	0.97 (0.28–3.32)	0.78 (0.33–1.86)	0.89 (0.32–2.43)	1.51 (0.56–4.04)	1.08 (0.38–3.08)
Men								
Managerial	1.23 (0.88–1.71)	1.22 (0.88–1.70)	1.38+ (0.99–1.91)	1.28 (0.93–1.78)	0.59 (0.31–1.13)	0.58+ (0.31–1.09)	1.31 (0.81–2.12)	1.21 (0.74–1.97)
Sales	1.45 (0.94–2.24)	1.44 (0.92–2.25)	1.97 (1.27–3.06)	1.76* (1.14–2.72)	0.77 (0.33–1.81)	0.73 (0.28–1.88)	2.03* (1.04–3.96)	1.73 (0.88–3.42)
Clerical	1.75 (0.98–3.12)	1.69+ (0.97–2.96)	2.35** (1.32–4.18)	2.05* (1.14–3.66)	0.90 (0.32–2.54)	0.70 (0.23–2.12)	1.88 (0.76–4.66)	1.54 (0.62–3.83)
Service	1.56+ (0.99–2.45)	1.55+ (0.97–2.48)	1.48 (0.83–2.64)	1.29 (0.73–2.30)	0.69 (0.74–2.98)	0.46 (0.16–1.31)	2.70** (1.37–5.35)	2.22* (1.09–4.55)
Farm and precision production	1.65** (1.14–2.38)	1.57* (1.05–2.35)	2.08*** (1.53–2.85)	1.68** (1.16–2.43)	1.49 (0.74–2.98)	1.11 (0.50–2.47)	2.90** (1.63–5.14)	2.10* (1.10–4.02)
Operators and laborers	1.72** (1.21–2.45)	1.66** (1.18–2.33)	1.82** (1.25–2.65)	1.51+ (0.98–2.28)	1.45 (0.74–2.98)	1.19 (0.56–2.52)	2.34** (1.42–3.85)	1.78* (1.05–3.02)

Note. Analyses were weighted using the 1992 HRS respondent weight. The unweighted sample size is 5,523. Reference trajectory is normal upward. Reference occupation is professional. Adjusted models include full set of controls.
Significance level: + $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.