YOU'RE FAT. HOW'S THAT MY PROBLEM? PREDICTING THE LIFETIME 3RD PARTY DIRECT COSTS OF OBESITY AMONG LATE ADOLESCENT MINORITIES WITH A RACE-SPECIFIC AGE-RELATED WEIGHT GAIN CURVE

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

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May 2019

ABSTRACT

There exists enormous variation in estimates of the lifetime cost of obesity by race. In order to justify policy measures to reduce obesity rates nationally, we must first discern the cost of doing nothing, so this question remains imperative and unresolved. Although several researchers have sought to quantify obesity's true cost stratified by race, none have produced *a race-specific* age-related weight gain curve, a vital component in producing an accurate estimate. This paper employs a Markov model of BMI category state changes separately for black and white males and females from ages 18 to 75 applied to updated estimates of obesity's costs and effect on mortality to quantify the median lifetime cost of obesity at age 18. It finds lower lifetime costs than previously, due largely to the staggering gain in weight among normal weight individuals, particularly among black males, that occurs in early adulthood.

BIOGRAPHICAL SKETCH

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ACKNOWLEDGEMENTS

Although no external financial support was needed for this project, I gratefully acknowledge the National Institute of Health, the US Department of Health and Human Services, and the Centers for Disease Control for providing public-use data for construction of the age-related weight gain curve, costs, and mortality information, respectively. I would also like to acknowledge Professors David Just and David Levitsky for their immeasurable patience and invaluable insight through this whole process.

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Introduction & Background:

Obesity imposes an immense financial burden on the United States' already-strained healthcare system with an extensive list of sequelae, including diabetes mellitus, hypertension, coronary heart disease, stroke, asthma, pulmonary embolism, gout, cancer, complications in spinal arthrodesis, and depression.[7–12] In addition to these issues, obesity in youth correlates with higher psychological stress and impaired skill development, although this issue remains etiologically unclear.[13–15] By the early 21st century, obesity had already become the second leading cause of preventable death in the US alongside tobacco, whose use has fallen precipitously among adolescents in recent years.[16]

Policymakers seeking to curtail the spread of this disease must consider the infeasibility of reaching every one of the over 100 million people affected by it nationally. As a result, any competent intervention strategy should target a high-risk demographic responsive to intervention. It appears black males and females in late adolescence could fit this mold, as they face disproportionately high rates of obesity, weight gain occurs fastest among this age group, and a large amount of evidence suggests late adolescents adopt permanent lifestyle changes at far greater rates than younger children.[1–6] However, in order to justify this intervention, we must first determine the lifetime costs of late adolescent obesity among black males and females in the US. Several researchers have sought to answer this question already; however, none have produced a race-specific age-related weight gain curve.

Hypothesized Relationship: Why does the age-related weight gain curve need to be "race-specific?"

The importance of a race-specific age-related weight gain curves in estimating obesity's costs becomes clearer when one dissects body mass index, or BMI, the indicator of obesity used in this and most other studies, which has several drawbacks. Measured as weight in kilograms divided by height in meters squared, BMI greatly overstates the adiposity of black males and females, who tend to have more fat free mass than their white counterparts, which could partially explain why black males and females generally face lower costs associated with obesity.[1,17] Black males and females with a BMI of 30 kg/m^2, for instance, may be healthier and less expensive than white males and females at the same level. However, they become obese at disproportionately higher rates than their white counterparts.[18] As a result, a generic age-related weight gain curve not separated by race would fail to account for the far greater weight gain of black people over the course of their lives. This becomes especially pertinent when one considers most estimates of age-related weight gain until this point have relied almost entirely on data for white Americans, which would cause a downward bias on the estimate of costs associated with obesity for black males and females.

Literature Review

Previous Approaches to Cost Estimation

A longitudinal dataset that perfectly tracks changes in weight and associated costs among the obese over time does not exist in this country. Therefore, any study seeking to estimate obesity's costs in the United States demands delicate interpretation and special attention paid to its assumptions. There exist three main types of study in the literature on obesity's costs: cross-sectional studies, which provide only a snapshot of a year or a few years of an obese person's life, but dominate the literature due to their simplicity, longitudinal studies that do not consider age-related weight gain, and longitudinal studies that control for age-related weight gain, but do not separate this curve by race.

Most Studies on Obesity's Costs are Cross-Sectional

While cross-sectional estimates allow us to understand the scope of the problem on a national scale, they reveal little of the actual cost of obesity. Obesity is a chronic and latent disease that becomes exponentially more expensive as the years spent with it increase, and so an arbitrary snapshot of a year or a few years of an obese person's life belies its true financial burden. The cross-sectional approach also cannot account for changes in weight or the cost of obesity's comorbidities over time, or differential life expectancies.[19] Still, a majority of the literature consists of cross-sectional studies, and so their results provide a useful starting place. All of the following studies have been inflated by the medical care component of the CPI to 2017 dollars.

The first and lowest estimates in the cross-sectional literature come from Population Attributable Fraction studies, which focus on how obesity affects the prevalence of diabetes mellitus, coronary heart disease, hypertension, gallbladder disease, osteoarthritis, and cancer.[20–22]

Using the 1988 and 1994 NHIS, Wolf and Colditz found only 5.7% of total national healthcare costs were attributable to obesity, but this estimate relied on old data when obesity had not yet reached crisis levels.[20] It also does not control for the fact that these diseases simply cost more for the obese than for normal weight adults because it relies on general disease cost estimates from other studies. Allison took the estimates of Wolf and Colditz and applied differential life expectancies, which resulted in a range of 0.89% to 4.32% of national healthcare costs attributable to obesity.[21] In order to create a more accurate estimate of obesity's costs, researchers next turned toward associative studies, which capture all of the costs associated with obesity instead of focusing only on a select number of diseases.

Some of the earliest and most widely cited associative studies on obesity's direct costs did not separate costs by race.[23–26] These studies used both the self-reported data from MEPS and from several other surveys, notably the Healthcare for Communities and NMES, or National Medical Expenditure Surveys. The results rely on older data, for which obesity's prevalence had not yet reached the immense levels of the present. Nevertheless, the average increase in annual medical spending associated with obesity ranged from $657 for inpatient and outpatient costs to $1,218 in total costs per year, which aggregates to 9.1% of national medical expenditures.[23,24] More significantly, for the first time in the literature, Finkelstein segregated costs by insurance status, and found that the public finances half of the burden of obesity.[24] These studies all relied on the costs of obesity among Americans of all ages. Having established a more robust estimate for obesity's costs through associative studies with differentiated costs by payer type, researchers next turned to the question of cost differences between races.

Wee et al. published the first race-specific associative study of the cost of obesity.[27] It used the 1998 MEPS data linked to NHIS data and ran a two-part model separately for blacks and whites. It found expenditures related to higher BMI rose for male and female whites as well as older adults but did not for blacks or people under age 35. In fact, while the obese face mean per capita healthcare expenditure of $6,932, well above the $4,751.62 spent by people of normal weight, they found no association at all between obesity and higher costs for blacks.[27] However, while pioneering, this study suffered from a variety of limitations, including possible bias from the retransformation of the two-part model; a relatively small sample of blacks; not accounting for costs above age 65, where obesity's costs begin to rise rapidly; and failing to account for potential confounding variables that bias costs for blacks such as socioeconomic status, healthcare utilization, and a lower life expectancy. In order to adjust for this hidden endogeneity, Professor Cawley experimented with an instrumental variable approach to truly discern the relationship of race and obesity's costs.[28]

The Medical Care Costs of Obesity: An IV Approach represents the highest and most realistic of the cross-sectional estimates, with annual excess costs of $4,030 ($3,554 third party) per obese person.[28] It used a subject's oldest child as an instrumental variable to account for the underestimate of costs associated with obesity among minorities, who tend to utilize healthcare to a far lower extent than the national average and suffer from disproportionately high rates of obesity. In fact, this study found almost identical costs associated with obesity between whites and blacks. This resulted in the highest burden of obesity in the cross-sectional literature by far, with $135.53 trillion, or 20%, of all healthcare costs associated with obesity.[28]

Longitudinal Studies generally don't include age-related weight gain

Longitudinal studies can theoretically account for the chronic nature of obesity and its comorbidities to produce far more accurate estimates. As noted before, there exist no datasets in the United States that track both BMI transitions over time and associated costs. The earliest studies dealt with this discrepancy by simply not including age-related weight gain, which produced a severe upward bias in estimates of the cost of adolescent obesity.[29–31]

The first attempt at modeling the lifetime costs of obesity focused on the relationship between BMI and five of obesity's comorbidities for men and women aged 35 to 64.[29,30] It employed simultaneous equations because the diseases act as risk factors for one another. Using the National Health and Nutrition Examination Survey, or NHANES III, and the Framingham Heart Study, Thompson employed a two-part model that first predicted the risk of each non-cardiovascular disease at different BMIs and then predicted the risk for coronary heart disease and stroke incorporating the results of the first equation. This study had a host of limitations, including the exclusion of race as a factor, older data and a non-comprehensive list of comorbidities, borrowing cost data for the diseases from different studies, only focusing on three age brackets, and completely excluding subjects with a BMI in excess of 37.5. Still, severely obese men aged 45 to 54 experienced $35,194 more in medical costs than their normal weight peers and women faced a similar increase.[29] Unfortunately, these initial "lifetime" estimates only measured until age 64. Naturally, researchers next explored the costs for older Americans, who tend to face far higher medical costs than middle-aged Americans.[32]

Several studies focus exclusively on the elderly, for whom more complete data exist than for any other age group due to their reliance on public insurance.[19,33,34] We will focus only on the most recent and robust estimate, which Yang and Hall authored in 2008. They rely on the Medicare Current Beneficiary Survey, which allows for the direct measurement of obesity in old age and its associated costs on a national scale. They then apply a simultaneous equation system approach to discern the cost of obesity among Americans aged 65 until death or 100. These equations determine how changes in bodyweight, chronic disease, functional status, longevity, and healthcare expenditure affect and are affected by one another. Unlike in previous studies, they found a significant difference between genders, with overweight and obese men facing 6-13% ($332,258 vs. $295,266) more lifetime healthcare expenditures than normal weight and obese women facing 11-17% more ($389,719 vs. $333,562).[19] Their use of a two-part model with a logged OLS model and a smearing retransformation could cause potential bias.[27,35] Yang and Hall also face many of the same limitations as previous studies on the cost of obesity for the elderly, namely not discussing the importance of race, short-run data, self-reported data, and the use of an assumption-heavy microsimulation model. Having found a competent estimate of obesity's long-term costs in old age, the next step was creating an associative study that separated by race, instead of the limited, racially unsegregated PAF studies conducted earlier, of its costs over the course of a person's life.

The first robust associative estimate of obesity's lifetime costs by race, Finkelstein found obese white males faced excess costs of $22,084 versus $33,552 for females, with obese black males and black females costing an excess of $17,764 and $18,850, respectively.[31] He applied the life expectancies from his previous work on MEPS data from 2001-04 and used the ubiquitous two-part model with a Gamma GLM with log link to determine total costs from age 18 until death. Although an otherwise competent estimate, Finkelstein's omission of age-related weight gain makes his results difficult to rank in terms of accuracy. Nonetheless, its abiding popularity and focus on race-specific costs demonstrates the study's influence. With age-related weight gain existing as a stark reality for which no study on lifetime costs had yet controlled, researchers began wondering how to account for its pervasive effects.

Longitudinal Studies that have age-related weight gain don't separate by race

In recent years, longitudinal studies have blended together several datasets that cover various years and populations to assemble an age-related weight gain curve. This provides a robust sample and the better estimates use measured height and weight, but because of a desire to increase the sample size, they do not differentiate the curve by race.[10,11,36–38] Therefore, none of the current studies provide a clear understanding of the plight of obese minority adolescents. Nevertheless, longitudinal studies with age-related weight gain curves have the capability of focusing more realistically on adolescent obesity's effects on costs, which provides far more useful results.

The first attempt at measuring the lifetime costs of obesity controlling for age-related weight gain relies on data from Burton et al. 1998 to project the lifetime cost of obesity from 20 to death.[36] It relied on a multitude of sources to derive cost data, which forces heavy reliance on the assumptions of others. Nonetheless, it pioneered the use of a semi-Markov state-transition model among simulated cohorts with a BMI of 24-45 and aged 20-65 and accounted for life expectancy discrepancies.[39] Still, the application of Heo et al. to control for age-related weight gain, which pieced together a variety of older data sources to predict BMI by age and sex *irrespective of race*, created only a generic age-related weight gain curve.[40] In general, Tucker found direct medical costs increased by 2.3% for each additional BMI unit above 25, but for younger blacks, as BMI exceeded 40 costs actually *fell*.[36] These paradoxical results undoubtedly occurred in part due to Tucker's over-reliance on the debatable assumptions of other studies and generic age-related weight gain curve.[31] Tucker played an important role in popularizing the desire to control for age-related weight gain, but further researchers would need to produce age-related weight gain curves based on more representative and current data.

In 2010, Wang et al. selected a cohort aged 16 to 17 to focus on because of late adolescent obesity's correlation with lifetime obesity.[37] They relied on the same life expectancy estimates as in Finkelstein's 2008 paper and applied the oft-used two-part model with a logit model then a GLM with log link focusing solely on 2000 MEPS data on costs after age 40. In order to control for age-related weight gain, they used the 1979 NLS Survey of Youth, which interviewed an older cohort that likely says little of the weight gain trajectory faced by children today, to track BMI changes over time. They found males cost $13,960 and females cost $12,646 more when obese in childhood.[37] The most apparent limitations are the age of the data, the use of only two points for BMI changes, only looking at costs after age 40, and assuming Americans maintain a constant weight after age 40. Wang et al. provided the first age-related weight gain curve produced from its own data and assumptions. In order to truly understand the effect of adolescent obesity on lifetime medical costs; however, researchers had to discern the costs for obese Americans under the age of 16.

Later that same year, Trasande used the Nationwide Inpatient Sample from 2005, an enormous survey-based dataset that documents over 7 million hospital stays, as well as the MEPS from 2002 to 2005 to calculate lifetime costs for children aged 12 until their death, which were $23,307 for males and $23,377 for females.[11] He accounted for age-related weight gain with the Fels Longitudinal Study, which began in 1929 and remarkably persists to the present.[41] Unfortunately, it primarily sampled white and suburban subjects, which makes estimating a race-specific age-related weight gain curve impossible. Additionally, Trasande only measured age-related weight gain at two points (ages 35 and 12), which again ignores the curve's nonlinearity.[11,40] Trasande also simply applied Finkelstein's cross-sectional study discussed in the previous section to find the costs based on BMI and BMI transition in adulthood, a poor choice given obesity's chronic nature. All of the above studies relied on age-related weight gain estimates derived from either older, unrepresentative datasets or at only two points in an obese American's life. Last year, Fallah-Fini pioneered the first age-related weight gain based on current data over the course of a person's life.[10]

Most recently, Fallah-Fini used a Markov model that found lifetime third party costs for a 20-year-old with obesity of $14,412 compared to $16,325 for those aged 50.[10] This discrepancy results from the discounting of future costs, most of which subjects face later in life. While still unseparated by race, Fallah-Fini's age-related weight gain estimate relied on the most recent and robust data available with the CARDIA study for weight gain below age 45 and ARIC for weight gain above 45. Unfortunately, the study only considers the comorbidity with the highest cost even if the subject has multiple, which likely substantially understates true costs. Additionally, the study only accounts for four obesity-related outcomes, has no racial component, and assumes disease independence. Still, for the first time a study modeled age-related weight gain over the course of an entire lifetime with current data, and the study demonstrated that state transitions most significantly burdened third-party payers.

Motivation

Numerous studies have sought to quantify both the direct and indirect costs of obesity. Unfortunately, the few that account for age-related weight gain, a pivotal part of any estimation, rely on older or unrepresentative datasets.[11,19,36,38–41] This becomes especially crucial as several studies have found that weight gain over time explains the majority of costs associated with obesity borne by third party payers.[10] More damning still, many of these estimates fail to account for the huge disparities in weight gain between races and produce estimates at only two ages, which does not properly represent the nonlinear shape of the trend.[11,13,27,36,37,42] Without this racial trend or using only a linear trend, these studies produce no practical interpretation of late adolescent obesity's costs for minorities. In order to rectify this omission, this study will create a race-specific age-related weight gain curve to produce the first lifetime estimate of obesity that considers the rapidity with which minority adolescents gain weight as they age. It will show that the costs faced by this group justify targeting them for intervention efforts.

Data

Criteria for Datasets in the Age-Related Weight Gain Curve

Unfortunately, the lack of a recent, robust estimate of race-specific age-related weight gain stems from the limitations of available racially diverse longitudinal studies in America. Ideally, this longitudinal dataset would be nationally representative, recent, and cover subjects from early adolescence until their deaths. Because such a dataset simply does not exist in this country, we created a list of criteria to determine whether a dataset deserves inclusion in this study despite its shortcomings. Most importantly, the dataset must contain a sufficient number of minority subjects to produce statistically powerful estimates. Other criteria include that the dataset covers over ten years of subjects' lives, is relatively recent, has sufficient follow-up and low attrition rates, covers a unique age range, has a short time between observations and objectively measured height and weight, and is nationally representative. The datasets that better fit these criteria received heavier weighting in the curve. All told, we made use of three datasets: the Framingham Heart Study (FHS), Coronary Artery Disease Risk in Young Adults (CARDIA), and the Atherosclerosis Risk in Communities Study (ARIC).

The Framingham Heart Study

Perhaps the most famous of the five major longitudinal population health studies in the United States, the Framingham Heart Study began with a predominately white cohort in 1948 in

Framingham, Massachusetts and continues to this day.[30] Unfortunately, the study did not begin reflecting the health trajectories of minority subjects until 1994, when the OMNI cohort was established to reflect Framingham's shifting demographics.[43] Despite biennial observations, FHS has several drawbacks, including covering too few minority subjects, representing only one city, covering minority subjects for just over 20 years, and having recent observations only for middle to older aged subjects. As a result, while a robust dataset with over 5,000 subjects even in the initial cohort, we decided not to use FHS to aid in the estimation of curves.[30] Instead, this data proved invaluable in testing the external validity of our methodology as a comparison group to white subjects in other datasets.

Coronary Artery Disease Risk in Young Adults

In an attempt to create a more representative sample, CARDIA, which began in 1985 and ended in 2005 with its fifth and final examination, observes the progression of Coronary Artery Disease in four population centers, including Birmingham, Chicago, Minneapolis, and Oakland.[45] The study enrolled over 5,000 black and white men and women from a variety of regional and sociodemographic situations, with 72% of the group remaining until 2005.[46] As one of the few nationally representative and racially diverse datasets available, the inclusion of CARDIA in our estimation was practically obligatory. CARDIA focuses predominately on the time period after 18 years of age until middle age.[10]

Atherosclerosis Risk in Communities Study (ARIC)

Analogously to CARDIA, ARIC takes subjects from four population centers: Minneapolis, Minnesota; Hagerstown, Maryland; Forsyth County, North Carolina; and Jackson Mississippi.[47] One of the largest longitudinal population health datasets in American history, ARIC, which began in 1987 and has conducted five examinations to date, boasts over 15,000 subjects pulled relatively evenly from each of these centers.[48] Because of its size, recency, and national representation, ARIC was included in the estimation of the curve and is weighted heavily. The dataset focuses primarily on subjects aged 45 to 64. Unfortunately, ARIC switched to phone interviews in 1998, at which point weight and height became self-reported and no longer fit the criteria for inclusion in this study.[10]

Data for Costs of Obesity

Medical Expenditure Survey (MEPS)

Beginning in 1996, the Medical Expenditure Survey, or MEPS, is the most detailed analysis of healthcare cost and utilization among noninstitutionalized Americans presently available. Far and away the most commonly used dataset for US medical expenditures, MEPS consists of a two-year panel design, where subjects report on diseases, health care costs, payment methods, and hundreds of other questions.[28] Unfortunately, although costs come directly from payers and households, subjects self-report height and weight. In order to account for this, we eliminated biologically implausible BMIs, which we defined as subjects with z-BMIs in excess of positive or negative four in accordance with the WHO's recommendations.[49]

We use data from the waves 2014 through 2016, with all costs inflated to 2016 dollars by the Medical Component of the CPI.[50] Because all costs focus on third party payers, we remove out of pocket costs from total expenditures. MEPS data makes use of a stratified multi-stage probability design to ensure subjects receive weights that make them nationally representative.[51] This cluster design, in which like subjects are grouped into strata, violates the independent and identically distributed observations assumption fundamental to the traditional calculation of standard errors.[52] We account for this cluster design through Stata's complex survey design tools, which correct for the unorthodox sampling plan, with singleton Primary Sampling Units caused by data sub setting centered to the overall sample mean to allow for variance estimation.[53,54] Additionally, because we pooled data from 2014 and 2016, we applied a standard correction recommended by both the CDC and in William G. Cochran's seminal book *Sampling Techniques* of dividing the weights by the number of years pooled.[55] This approach also makes intuitive sense because since each survey represents the entire nation, any additional year added would cause the weighted observations to double the population of the country.

Differential Life Expectancies Data

Public Use National Health Interview Survey (NHIS) and Corresponding Linked Mortality Files

Commissioned by the US Census Bureau, the NHIS studies a range of health behaviors and characteristics. Recently, the National Center for Health Statistics (NCHS) has made public-use Linked Mortality Files (LMFs) available through the year 2014 that utilize data from the NHIS to link to files from the comprehensive National Death Index. As a result, we make use of data from the years 1997 to 2014 in an effort to update recent work on life expectancy that relied primarily on data from the 1990s. Although public use data is subject to data perturbation for anomalous causes of death and location censoring, our predominant focus on only vital status renders these limitations bearable. Our primary concern in using these data is self-reported height and weight, but these limitations remain a stumbling block for all researchers.

National Lifetables

In order to provide a basis from which to create BMI-specific life expectancies, we use the official 2015 US Lifetables provided by the NCHS and separated by race and gender. We will apply hazard ratios associated with different levels of BMI to these estimates to discern the impact of BMI on life expectancy separately by race and gender.

Methodology[1]

Estimating Age-Related Weight Gain

Formal Model Specification

$$\varepsilon_{t+1} = P\varepsilon_t + v_{t+1} \tag{1}$$

Where ε_{t+1} is current time period, ε_t is previous time period, and v_{t+1} is the innovation, which should have a mean of zero and random variance (White Noise Process) if the forecast is robust.[56]

We make use of a four-state Markov model to estimate age-related weight gain over the course of each subject's life. The states consist of the widely-agreed upon BMI categories for underweight (under 18 kg/m^2), normal weight (from 18 to 25 kg/m^2), overweight (from 25 to 30 kg/m^2), and obese (greater than or equal to 30 kg/m^2).[57] Four different iterations of the model exist in total, with subjects separated both by gender and race. A Markov process is "memoryless" in the sense that the only data used to make an estimation are from the previous state, which means it can be represented by the First Order Difference Equation below:[58,56]

$$x_{k+1} = Px_k \tag{2}$$

Where x_{k+1} represents the next observation, x_k represents the current state, and P represents a stochastic transition probability matrix

This modeling technique has a long history in the study of BMI transition estimation,[10,36,38,59] but also makes sense to use intuitively. Because of the relative intractability and consistency of age-related weight gain, a subject's weight in the last time period likely correlates extremely powerfully with their current weight.[60] An obese or overweight adult rarely goes back down to a lower BMI category, and almost never sustains this weight loss, which makes their history of weight prior to the latest period largely irrelevant.[34] Moreover, our decision to use a relatively short gap of three years between observations suggests BMI likely

[1] Note: In an effort to encourage reproducibility and transparency, both the age-related weight gain curve and cost estimates were run on randomly generated data, and then posted on Open Science Framework.

changes only gradually from the previous time period and multiple state transitions in such a short period of time seem unlikely. These state transitions for subjects allow us to form a stochastic state transition probability matrix, from which the probability of shifting from one BMI category to another based on current BMI and age can be elucidated over the course of every subject's life.

An advantage of our approach compared to some of the existing literature is that we let the data dictate the formation of these state transition probability matrices instead of relying on previous estimates, which introduce potential bias from the imperfect study designs of others and are often less current.[10,13,61] As discussed earlier, we tested the external validity of the model with an out of sample group of white males and females in the FHS.[42] All estimates are state and age-specific, with pregnant subjects dropped and no other covariates. The country's recent secular trend in weight gain, wherein people of every age weigh more than they did previously, could introduce bias.[62] However, because we construct these curves from observations of real people over time and more recent observations receive heavier weighting, it still serves the purpose of accurately modeling real world weight gain trajectories.

In order to calculate 95% confidence intervals, we performed 1,000 bootstrapped iterations of the original state transition intensity matrix and plotted the confidence intervals on a histogram to ensure the iterations achieved maximum likelihood (through the production of bimodal distributions). We had to bootstrap because our confidence intervals came from the Hessian matrix for asymptotic standard errors, with the asymptotic approximation becoming more accurate as the iterations increased, although negligibly past 1,000 iterations.

Age-related Weight Gain Curve Weighting and Age Groups

Because of both data limitations and similarities in weight gain between certain ages, we grouped subjects in each dataset into age categories. We determined these age categories both by biological intuition and data availability. CARDIA, which has subjects aged 18 to 55, allowed for relatively large age brackets. Because ones individual health behavior remains largely stagnant after their twenties, there exists a great deal of consistency between one's twenties and thirties, and so the first age group is from ages 18 to 35. Although one's metabolism generally slows and testosterone declines around thirty, these effects tend to take years to fully play out.[65] Similarly, the next age group, 36 to 45, consists of people in similar life circumstances and biological realities. The final CARDIA group, aged 46 to 55, attempts to capture changes in weight that may result in being at the advanced stage of one's career.

Lastly, ARIC, which covers subjects aged 44 until their late nineties, produces a decade of overlap with CARDIA. Because of CARDIA's more recent data (up to 2011 compared to 1998), it receives weighting of 70% compared to 30% for ARIC. The overlapping group, ages 44 to 55, produced relatively consistent estimates between the datasets, so the exact level of weighting matters little. ARIC adds the age groups 56 to 64 and 65 to 74. Unfortunately, none of the datasets provide a sufficiently large sample for estimates above 75 years of age. As a result, we transition subjects to their original BMIs at this point, which is an assumption that requires further analysis.

In order to generate median estimates, we took the total product of the probability of remaining in the current BMI status every three years until this number declined to less than 50%, at which point a subject transitioned to the next most probable state. These estimates are contrasted with the upper and lower bounds of the 95% confidence interval in the appendix.

Estimating Obesity-related Costs

As is convention with highly skewed healthcare data, we run a two-part model (2PM) on the probability of any medical expenditures and then the total medical expenditures conditional on having any.[28,26,27,66-67,19] We chose this model because the large number of subjects with no medical expenditures in any given year would severely bias our results with only one model on total medical expenditure. We control for MEPS's complex survey design as described above, so all standard errors and confidence intervals are subject to this adjustment.

For the first part of the model the dependent variable, whether a subject reports any medical expenditure, will have a binomial distribution.[2] In order to regress a binary variable, we use a generalized linear model, where a link function transforms the binomial distribution into an approximately normal distribution. The two most popular versions of this model are the Logit and Probit. There exist relatively few practical differences between these models: a logistic error term's distribution normally has a higher kurtosis, interpretations of the coefficients vary, and slight differences in model fit exist. Because the distinction matters little, we decided to use a logit model because of its marginally superior fit and relative ease of interpretation.

First Equation

$$\boldsymbol{P(Medical\ Expenditure_i = 1)}$$

$$= \frac{e^{X\beta}}{1+e^{X\beta}} \tag{3}$$

$$\boldsymbol{X\beta = \beta_0 + \beta_1 BMICategories_i + \beta_2 Education_i + \beta_3 Rural_i + \beta_4 Smoker_i + \beta_5 InsuranceStat_i + \beta_6 Education_i + \beta_7 MarriageStat_i + \beta_8 Region_i + \beta_9 Age_i + \beta_{10} BMICatsXAge_i + \beta_{11} Age^2_i + \beta_{12} Age^3_i + \beta_{13} Preg_i + \varepsilon_i}$$

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[2] $P(X = x) = \sum_x^n \binom{n}{x} p^x (1-p)^{n-x}$ Binomial Probability Mass Function. N options choose x at the beginning of the formula suggests a constant level of n and x, which is because an experiment is conducted under identical conditions (or "with replacement").

Our decision on the functional form of the second part of the model proved more nuanced. The two most commonly used modeling approaches are a Generalized Linear Model (GLM) with a Gamma Log Link and a Logged OLS regression. These discussions can sometimes feel a bit murky, so we think a helpful analogy to understand the distinction between a GLM and an OLS model is the difference between a rectangle and square. An OLS model is a GLM *that requires a normal (or in this case lognormal) distribution*, like how a square is a rectangle that requires equal side lengths, whereas in the general case a GLM, like how a rectangle does not require a square's assumptions, can fit with both normal and non-normal distributions. Thus, the GLM requires no retransformation and has more relaxed assumptions than an OLS model, such as not requiring a lognormal distribution, but provides less statistical efficiency. Meanwhile although a logged OLS model brings in the upper tail of the distribution and accounts for the extreme range of healthcare data to some extent, it also requires a smearing retransformation, which could cause bias in the presence of heteroskedasticity.[68] We used a histogram of expenditure data and ran Park tests to determine that the lognormal distribution fit the data best, so we chose the logged OLS model.

Second Equation

$$\boldsymbol{Logged\ Conditional\ Medical\ Expenditures = X\beta} \quad (4)$$

$$X\beta = \beta_0 + \beta_1 BMICategories_i + \beta_2 Education_i + \beta_3 Smoker_i + \beta_4 InsuranceStat_i + \beta_5 MarriageStat_i + \beta_6 Region_i + \beta_7 Age_i + \beta_8 BMICatsXAge_i + \beta_9 Age^2{}_i + \beta_{10} Age^3{}_i + \beta_{11} Preg_i + \varepsilon_i$$

We run the 2PM separately by race and gender, with all medical expenditures inflated to 2016 dollars through the medical component of the CPI and discounted at a 3% discount rate over the course of a subject's life.

Variable selection was identical between the two equations. We control for education through Bachelor's and Graduate Degree dummy variables, whether a person smokes, their current insurance status (with uninsured as the omitted category), their marital status (with single as the omitted category), their census region (with South as the omitted category), their age as a continuous variable, an interaction between their BMI category and age, quadratic and cubic age variables, and a variable for whether a person is currently pregnant. The key variable, BMI category, relies on the same categories as described earlier (underweight, normal weight, overweight, obese), with obese as the omitted category.

Differential Life Expectancies

Naturally, a lifetime cost estimate must control for the possibility that obese people do not live as long as their normal weight counterparts and, hence, cost less. Unfortunately, the existing literature on the life expectancy penalty resulting from obesity relies on largely older data and has provided equivocal results. In fact, some studies even found an "obesity paradox" among black males, wherein the obese outlive those of normal weight.[36] This undoubtedly has to do with some form of endogeneity, and we cannot preclude such an issue from existing in our own study. However, to provide an authoritative and more recent view of the subject, we have decided to update life expectancies by using interview data from 1997-2014 with mortality follow-up through 2015, the latest time period used for such a study to date.

We first found the age-specific death probabilities of black and white men and women in the official 2015 US Lifetables published by the NCHS.[69] Unfortunately, these data do not account for specific BMI categories and smoking status, an enormous potential confounder in life expectancy. As a result, we created a Cox proportional hazards model run separately by race and gender with NHIS data from 1997-2014 and linked it with corresponding Linked Mortality Files in the National Death Index until 2015. The output produced by a Cox proportional hazards model, a hazard ratio, illustrates the changed hazard of an outcome occurring from a change in characteristics. For instance, a hazard ratio of three for an obese person would suggest that they have triple the chance of dying that year compared to a reference normal weight person with otherwise identical attributes. Thus, in order to determine BMI's effects on life expectancy by age, we will apply the hazard ratios of each BMI and smoking category to the probability of death at any age.

Once again, the complex survey design and clustering necessitated the use of complex survey design commands in Stata. However, because the sample design changed in 2006, we also had to alter the strata and primary sampling units to maintain statistical independence between these differing sampling plans. Additionally, the pooling of nationally representative data over 18 years required us to divide the weighting variable by the number of years in the pool, as detailed previously. The end result was a survey of 500,121 respondents, of whom 61,552 died by the year 2015.

We applied the same BMI categories as used in the rest of the study; however, we also had to account for smoking as a potential confounder. We classified people as never smokers, current smokers, or, if they smoked at least 100 cigarettes in their lives, former smokers. The covariates were the BMI categories with normal weight as the reference group, smoking status with never smokers as the reference group, and interaction terms between disproportionate BMI groups (which varied by race) and age, since the effects of smoking and BMI both tend to diverge later in life.

Unlike in previous work, we found several points at which the proportional hazards assumption would be violated according to Schoenfeld residuals and log-log plots.[31,39] There exist two common methods for handling disproportionality – an interaction between the violating variable and time and stratification by the variable.[70] Because stratification does not allow for estimation of a parameter value (and we need such a value to accurately assess life expectancy effects) and causes less efficiency, we added interaction terms between age and each violating variable. This adjustment also makes intuitive sense, as BMI's impact differs markedly based on one's age and time spent in each state, so age interactions should provide a more precise estimation of its impact on survival probability over time.

After conducting likelihood ratio tests for the interaction model and Wald tests for the joint significance of the interaction variables and analyzing AIC and BIC criterion for goodness of fit, we confirmed the logic behind this intuition. In the interest of comparability with Finkelstein's article, which focused on data from 1988 to 2002, we also ran the model for the years 1990 to 2005 (excluding 1996 for lacking smoking data) and attached the results in the appendix.

Cox Proportional Hazards Model

$$h(t) = h_0(t)e^{(X\beta)} \tag{5}$$

where $X\beta = \beta_0 + \beta_1 Age + \beta_2 Age^2 + \beta_3 BMICats + \beta_4 SmokingStat + \beta_5 AgexSmokingStat + \beta_6 AgexBMICats + \varepsilon$

$h_0(t)$*=reference group (normal weight person with otherwise identical characteristics)*

$h(t)$ *= hazard ratio*

Before we could apply these hazard ratios to the lifetable to create BMI-specific death probabilities, we had to determine the probability of being in each BMI category by age. Thus, we created a multinomial logit with the 12 possible combinations of BMI category and smoking status as the dependent variable and age, age squared, and age cubed as the independent variables. These estimates reflect the most recent national prevalence rates and, hence, rely on data pooled data from 2012 to 2014. They were not run separately by age group due to an insufficient sample size and desire for an efficient estimate.

Multinomial Logit on Probability of Being in Any Particular BMI Category

$$\boldsymbol{P_{ij}} = \frac{\boldsymbol{e^{(\alpha + X_{kj_i}\beta_{kj})}}}{\boldsymbol{1 + \sum_{j=1}^{J} e^{\sum_{j=1}^{K} \alpha + X_{kji}\beta_{kj}}}} \quad (6)$$

$$\boldsymbol{X\beta = \beta_0 + \beta_1 Age_i + \beta_2 Age^2_i + \beta 3 Age^3_i + \varepsilon_i}$$

We calculated BMI-specific death probabilities for each race and gender group by multiplying the unadjusted probabilities in the lifetables by an adjustment factor. This adjustment factor equaled the hazard ratio of a particular BMI and smoking-status at a specific age divided by the sum of the product of the hazard ratios and probability of being in each BMI and smoking status category for that same age.

$$\hat{\theta}_{ijk} = \theta_j \frac{h(t)_{ijk}}{\sum_{k=1}^{3} \sum_{j=1}^{4} P_{ijk} h(t)_{ijk}} \quad (7)$$

After collecting these death probabilities, we simply took the product of the survival probabilities at each age (1-$\hat{\theta}_{ijk}$) until the cumulative probability of survival became less than 0.5 to produce median life expectancy. We then subtracted the life expectancy of an obese person from that of a normal weight person with otherwise matching characteristics to produce Years of Life Lost (YLLs) from obesity for each smoking category. Table 2 illustrates these results by smoking status, although we will focus on the effect on non-smokers for the sake of consistency.

Results

Table 1. Cost at each age given Median Life Expectancy (3% discount rate) Unadjusted by Age-Related Weight Gain

BMI Category Starting At Age 18	Normal Weight Lifetime Cost	Obese Lifetime Cost	Excess Costs
White males	$32,916.76	$50,193.48	$17,276.72
Black males	$33,589.55	$41,720.27	$8,130.72
White females	$32,858.00	$58,255.65	$25,397.65
Black females	$22,951.34	$34,989.13	$12,037.79
Starting At Age 40			
White males	$48,021.44	$78,421.38	$30,399.94
Black males	$43,467.89	$68,818.14	$25,350.25
White females	$40,549.27	$78,302.17	$37,752.90
Black females	$31,297.40	$62,538.71	$31,241.31
Starting At Age 60			
White males	$58,056.10	$96,336.95	$38,280.85
Black males	$36,974.82	$75,160.80	$38,185.98
White females	$45,235.87	$88,923.10	$43,687.23
Black females	$34,989.13	$73,844.98	$38,855.85

Note: Range from Survival Probabilities presented in parentheses
*Numbers are for single, not pregnant non-smokers w/ public insurance

Unadjusted Cost Estimates

Given the complexity of the methods that have produced our estimates, we have decided to focus the results section on a case study of obesity's lifetime effects: a publicly insured 18-year-old of each race and gender who is normal weight compared to an otherwise identical obese teenager. Table 1 suggests that our excess cost estimates for white males and females before applying age-related weight gain are only somewhat conservative compared to the existing literature. However, black males and females face markedly lower excess costs than past estimates suggest. This likely has to do with our decision to focus on people of identical insurance status, as the high number of black males and females who remain uninsured would otherwise skew our estimate of obesity's true cost. Because of cost discounting, the cost for every group becomes higher the later in life they remain obese, with the immense disparity in excess costs faced between races disappearing entirely by age 60. Unfortunately, the discrepancy among younger people by race probably results from a lower level of healthcare access and utilization among black compared to white people.[71] However, obesity's prevalence nationally among black males and females remains substantially higher than for their white counterparts.[5] Additionally, if our age-related weight gain curves suggest a higher rate of persistence among blacks suffering from obesity, these estimates could prove misleading regarding obesity's true cost within the black community. For full cost regression results, consult the appendix.

Table 2: Median Life Expectancy Comparison									
Life Expectancy at Age 18									
	Never Smokers			**Current Smokers**			**Former Smokers**		
	Normal Weight	Overweight	Obese	Normal Weight	Overweight	Obese	Normal Weight	Overweight	Obese
Black Males	76	80	78	68	71	69	73	76	75
White Males	82	84	81	72	74	70	79	81	78
Black Females	82	84	82	75	77	74	80	82	80
White Females	86	86	84	77	78	75	83	83	81
Note: "Protective" Result for Obese Black Males likely due to Endogeneity									

Unadjusted Life Expectancy Estimates

Although smoking remains more damaging in terms of life expectancy effects, obesity causes a loss of at least one year of life at age 18 for every group except black males, for whom obesity appears protective. This spurious result has occurred elsewhere in the literature and probably results from some form of endogeneity, wherein obese black males have certain characteristics that serve to counteract the disease's deleterious effects.[36] Additionally, unlike previous articles that explored the impact of obesity levels beyond 30, data constraints for our age-related weight gain curve force us to focus on even the relatively mild cases with sub-35 BMIs. Obese white females face the harshest survival penalty of two years of life lost at age 18 regardless of smoking status, while white males consistently face a loss of one year and black females face a loss of several months to a year depending on smoking status. Like the cost estimates, these life expectancies appear somewhat conservative in measuring obesity's impact compared to previous attempts. While this could simply be an artifact of the data, there also exists a real possibility that an ever-improving repertoire of medicines to combat obesity's comorbidities that have proliferated over the previous decades has caused this decrease in obesity's lethality.[72]

Age-Related Weight Gain Estimates

The two-period moving average graphs in the appendix depict BMI state transitions from age 18 until 75 for each of the four race and gender groups, as well as the upper and lower bounds of the 95% confidence intervals. Although the graphs look broadly similar, one of the most powerful results occurs among normal weight black males. While the other three groups have a lower bound confidence interval that lags slightly behind the point estimate of weight gain, the lower bound and point estimate among normal weight black males move in lockstep until middle age. The remarkable precision of this estimate indicates a degree of inevitability in weight gain unique to black males. However, more worryingly, normal weight black males and females share a steep gain in weight during their mid-late twenties, and subsequently become obese an average of a *full decade* before their white counterparts. For the transition probability matrices, consult the appendix.

Table 3: Median Life Expectancy Comparison		
Life Expectancy at Age 18 With Age-Related Weight Gain		
	Never Smokers	
	Normal Weight	Obese
Black Males	79	79
White Males	82	83
Black Females	83	82
White Females	85	84
Note: "Protective" Result for Obese Black Males likely due to Endogeneity		

Age-Related Weight Gain Adjusted Life Expectancies

After incorporating the age-related weight gain trajectories into the previous life expectancy estimates from age 18 until death, the survival gap between obese and normal weight people lessens considerably. Previously enjoying a survival advantage of 2 years, obese black males now live an identical amount of time as if they were normal weight. This result stems from the speed with which the average black male of normal weight becomes overweight and then obese, which means both groups spend the majority of their lives obese. On the other hand, obese white males actually gained a survival advantage over their normal weight peers of one year. This is undoubtedly the product of obese males temporarily moving back down to the overweight category, the group with the highest overall life expectancy. Obese black females faced a decreased life expectancy of only a few months, while obese white females now have a life expectancy disadvantage of only one year.

Table 4. Cost at each age given Median Life Expectancy (3% discount rate) Adjusted by Age-Related Weight Gain

BMI Category Starting At Age 18	Normal Weight Lifetime Cost	Obese Lifetime Cost	Excess Costs
White males	$42,039.61	$50,029.33	$6,989.72
Black males	$40,625.02	$36,652.95	$3,972.07
White females	$42,827.32	$53,374.53	$10,547.21
Black females	$34,503.88	$40,573.42	$6,069.54

Note: Range from Survival Probabilities presented in parentheses
*Numbers are for single, not pregnant non-smokers w/ public insurance

Final Cost Estimates

After adjusting for age-related weight gain, the excess costs associated with obesity fell for each group, with only obese white women facing excess costs beyond $10,000. These results put our excess cost estimates far below most other work in the literature. However, this result speaks more to the latent, backloaded nature of obesity's costs and the effect of cost discounting. For instance, an obese 76-year-old black male faces undiscounted medical expenses in excess of $5,000 *in a single year.* However, discounting from 18 years of age decreases this effect to just over $1,500. Likewise, because black males live significantly shorter lives than their white counterparts, they have less time over which to accumulate more medical expenses. Medical professionals, public health advocates, and community organizers across the country have worked ardently to reduce this health disparity, which should only increase the cost of obesity in the future. If black males lived as long as their white counterparts, they would face additional discounted excess costs of $4,173.64, or $8,145.71 in excess costs total. The somewhat lower cost of obesity among black males should be viewed as a sign of our nation's public health shortcomings rather than as a justification for complacency. Additionally, when dissecting these estimates, one must recall that age-related weight gain did not lower the immense cost of obesity, rather, it elevated the true cost of the disease given the remarkably high probability that anyone regardless of race or sex will eventually become obese.

Limitations

These results present several limitations and avenues for further research. Firstly, it appears the decision to use 30 BMI as a cutoff for obesity has caused conservative estimates. Likewise, our decision to bin ages and BMI categories, while necessary, does reduce the efficiency of the estimate. Additionally, because there exists no dataset with which we can determine time spent with obesity, which research has shown to substantially increase costs, these estimates should be viewed as an absolute lower bound.[73] We also rely on median estimates of state transition, but weight gain trajectory remains a highly individual process, and simulation studies should be performed to determine the impact of a change in assumptions on weight gain. Lastly, our age-related weight gain only went until age 75, after which some of the most vital years of life in terms of cost occur.

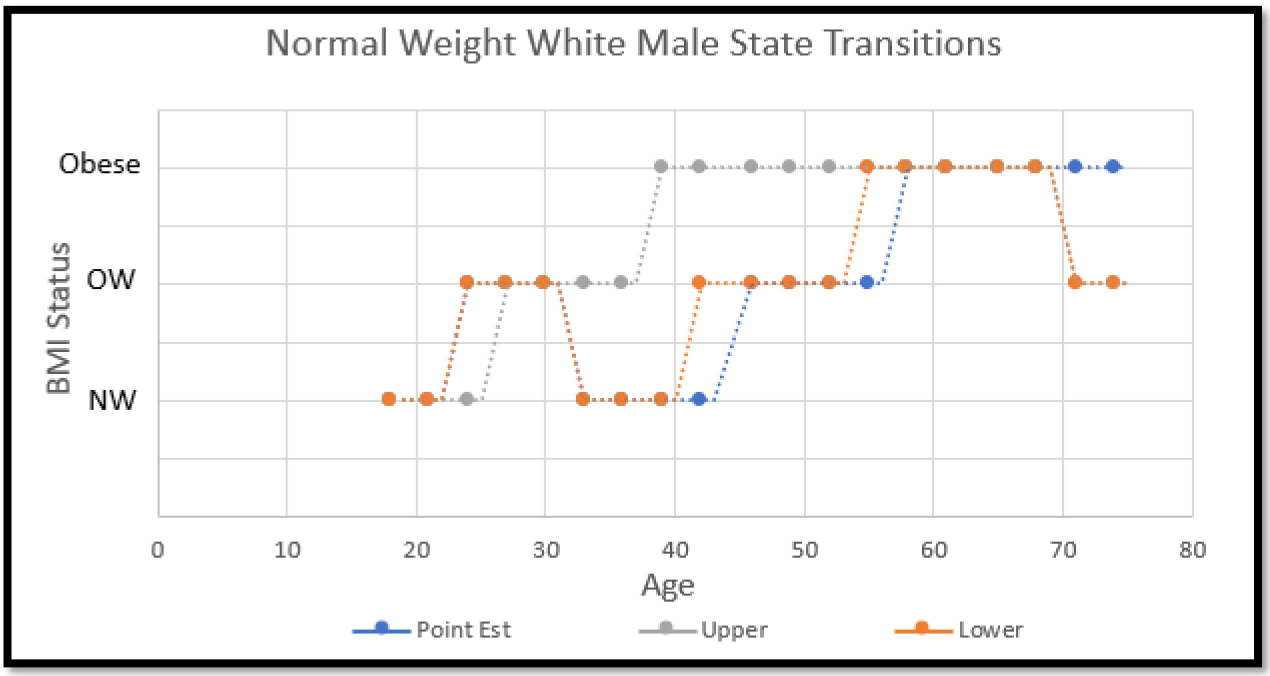
Discussion

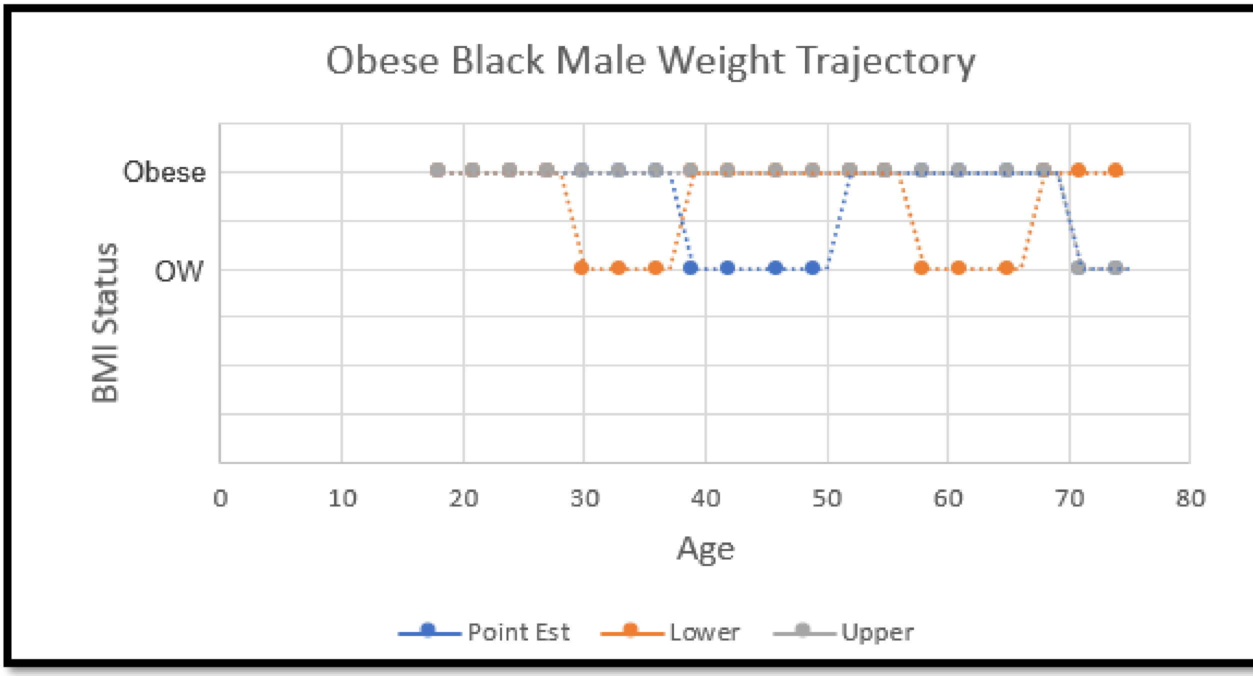
This estimate provides policymakers context for a conservative cost-benefit analysis of obesity-focused interventions. We discovered that, while record numbers of adolescents suffer from obesity, an enormous portion of obesity's prevalence, and therefore cost, comes from age-related weight gain in early adulthood. The situation appears especially dire for normal weight black males and females at age

18, who on average face the prospect of obesity *a full decade before* their white counterparts. When other studies rely only on white subjects to estimate age-related weight gain, they miss this fact entirely and subsequently overestimate the lifetime cost of late adolescent obesity and underestimate the cost of normal weight black males and females, for whom facing obesity later in life is almost an inevitability. This suggests that the issue of differential obesity levels between white and black males and females remains a problem even after adolescence, and further research should be conducted to discover the determinants of this weight gain later in life and whether preventative efforts in adolescence to reduce obesity in later life among black males and females could prove feasible. Unfortunately, the relatively low cost of obesity among black males also points to an area in serious need of continued research: health disparities between races. Black males live shorter lives and gain weight at faster rates than any of the other groups analyzed, which suggests health outcomes in this country still run strongly on racial lines. Far from a justification for complacency in the face of the obesity epidemic, these lower lifetime costs of late adolescent obesity speak to the troubling persistence of the threat of obesity throughout the lives of black males and females, which will require enormous creativity from policymakers to rectify.

APPENDIX


Obese White Male State Transitions
BMI Status
Obese
OW
NW
0
10
20
30
40
50
60
70
80
Age
Point Estimate
Upper Bound
Lower Bound


Normal Weight White Male State Transitions
BMI Status
Obese
OW
NW
0
10
20
30
40
50
60
70
80
Age
Point Est
Upper
Lower


Obese Black Male Weight Trajectory
Obese
OW
BMI Status
0
10
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40
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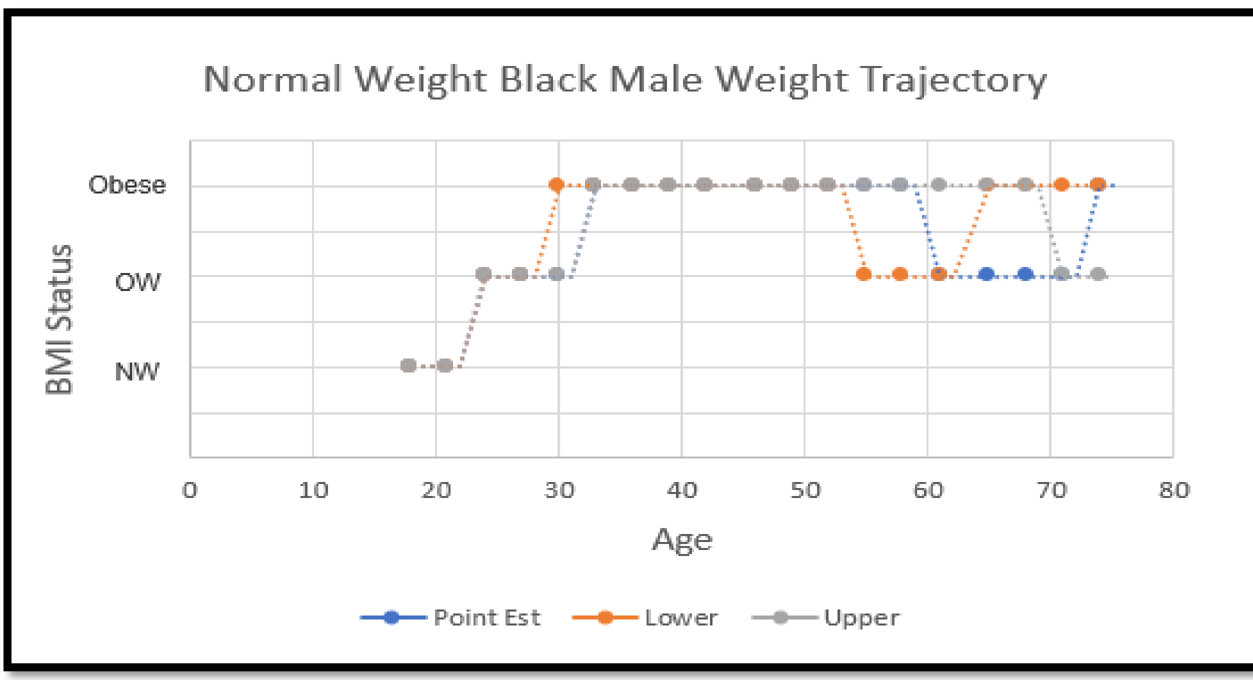
80
Age
Point Est
Lower
Upper


Normal Weight Black Male Weight Trajectory
Obese
OW
NW
BMI Status
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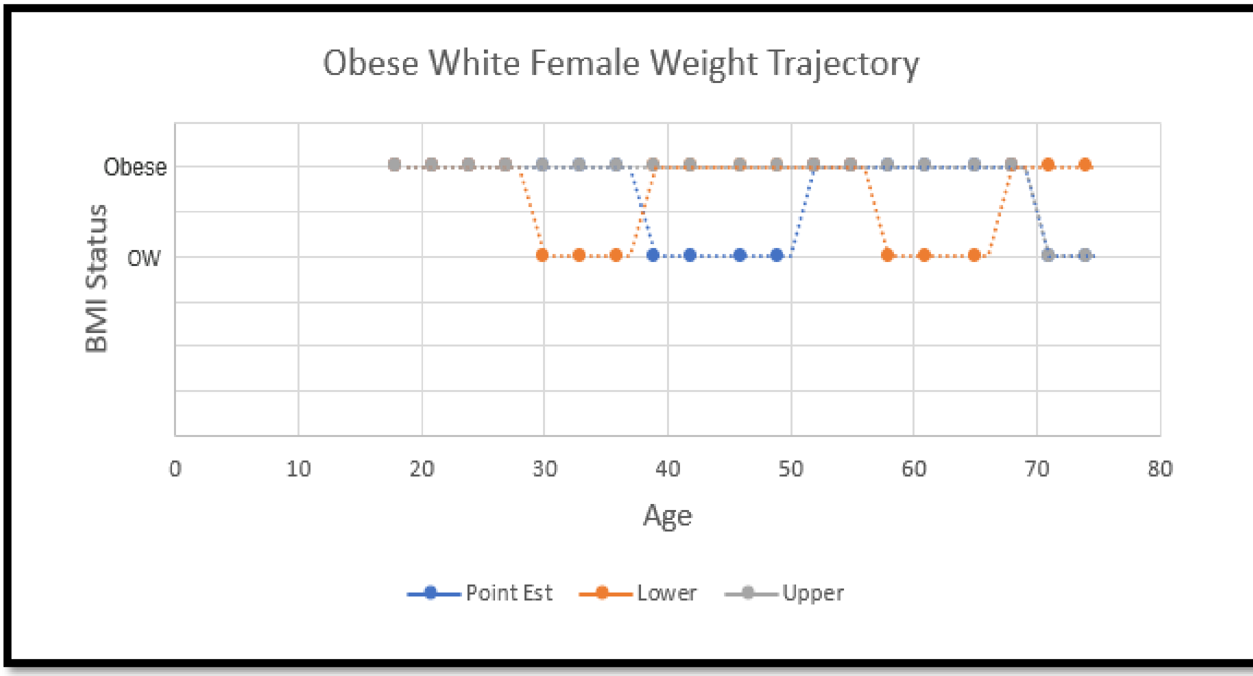
Age
Point Est
Lower
Upper


Obese White Female Weight Trajectory
Obese
OW
BMI Status
0
10
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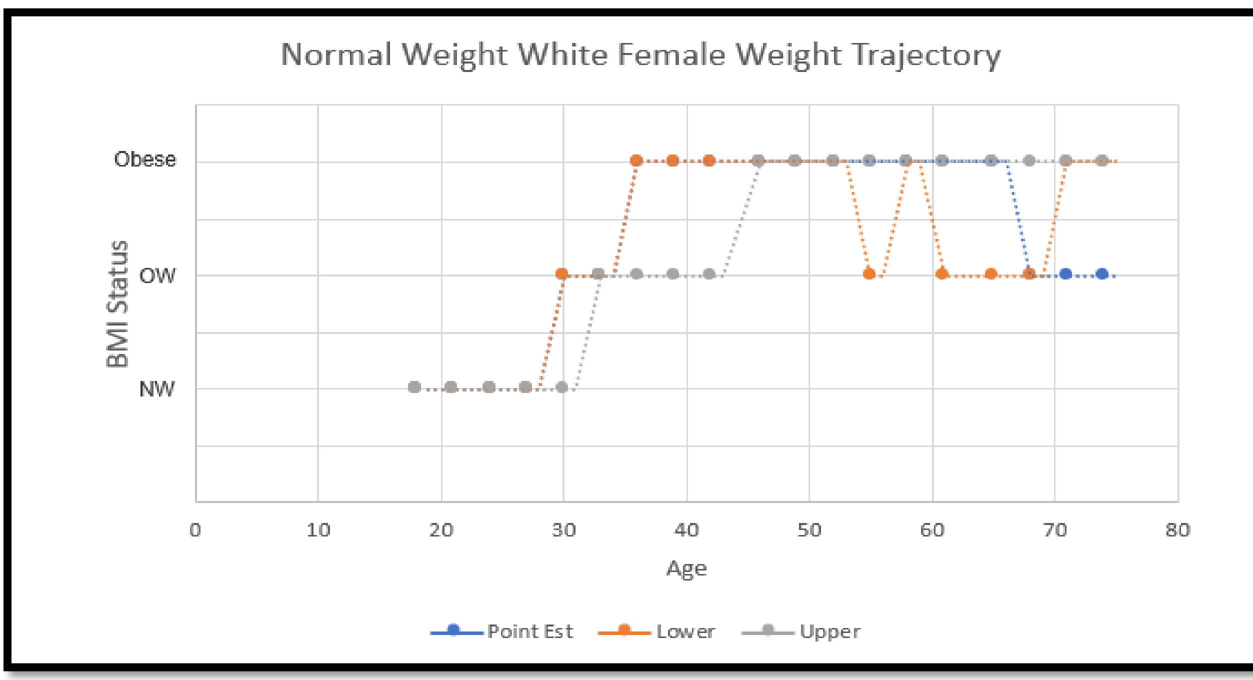
70
80
Age
Point Est
Lower
Upper


Normal Weight White Female Weight Trajectory
Obese
OW
NW
BMI Status
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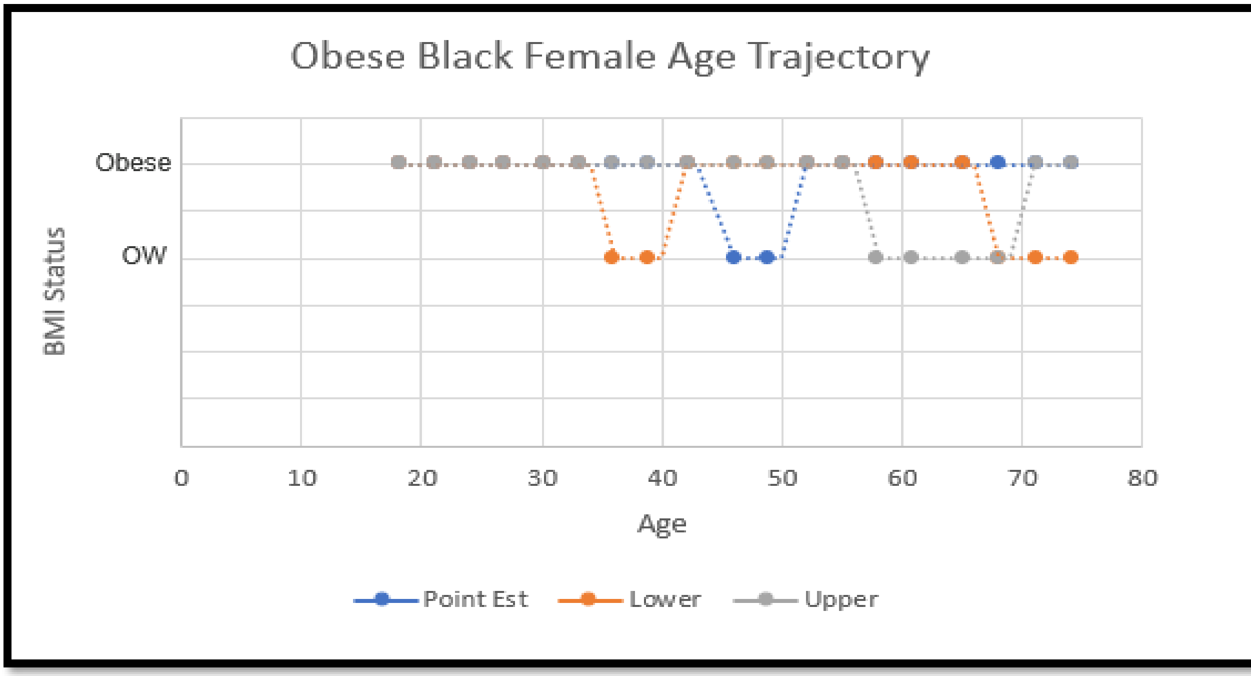
Age
Point Est
Lower
Upper


Obese Black Female Age Trajectory
Obese
OW
BMI Status
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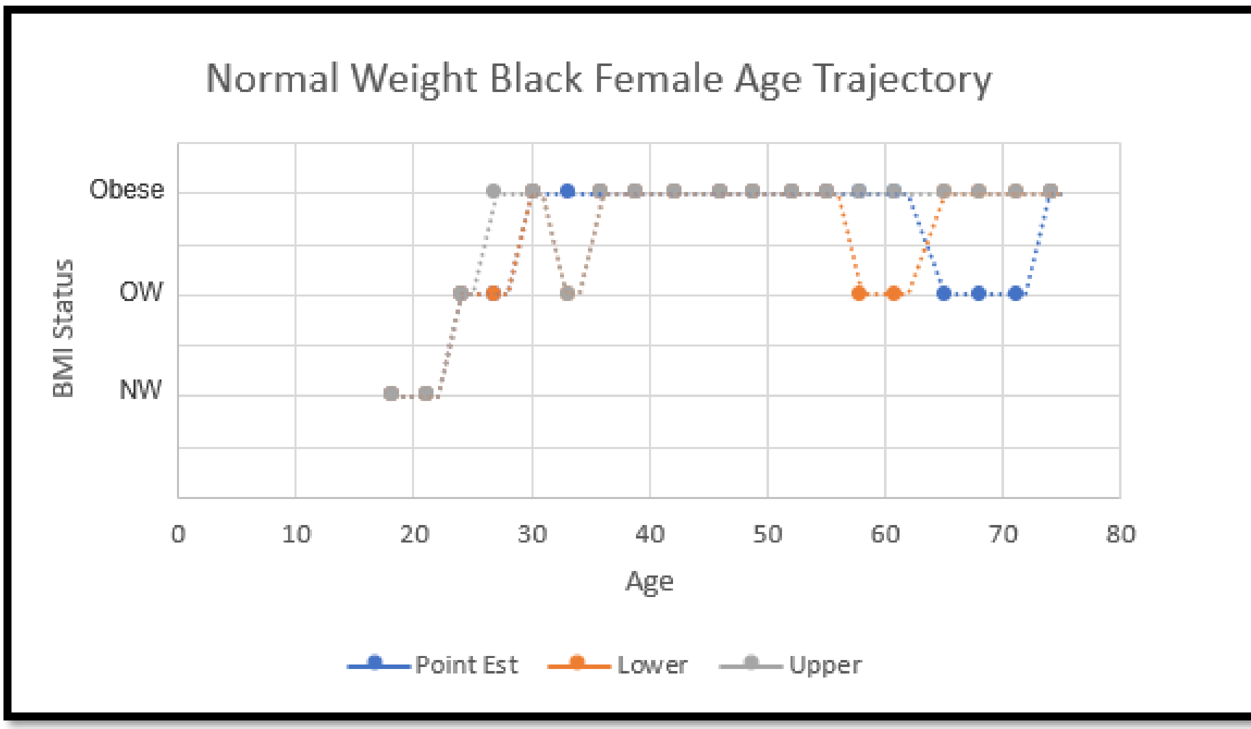
Age
Point Est
Lower
Upper


Normal Weight Black Female Age Trajectory
Obese
OW
NW
BMI Status
0
10
20
30
40
50
60
70
80
Age
Point Est
Lower
Upper

Transition Probability Matrices

Black Males Ages 18 to 35

From/To	*Underweight*	*Normal Weight*	*Overweight*	*Obese*
Underweight	0	0	0	0
Normal Weight	0	0.77 (0.75, 0.79)	0.20 (0.18, 0.22)	0.03 (0.02, 0.03)
Overweight	0	0.08 (0.06, 0.10)	0.72 (0.69, 0.75)	0.20 (0.17, 0.22)
Obese	0	0.006 (0.004, 0.008)	0.09 (0.07, 0.12)	0.90 (0.87, 0.92)

White Males Ages 18 to 35

From/To	*Underweight*	*Normal Weight*	*Overweight*	*Obese*
Underweight	0	0	0	0
Normal Weight	0	0.80 (0.78, 0.82)	0.19 (0.17, 0.21)	0.01 (0.01, 0.02)
Overweight	0	0.12 (0.10, 0.14)	0.77 (0.75, 0.80)	0.11 (0.09, 0.13)
Obese	0	0.008 (0.005, 0.01)	0.11 (0.07, 0.14)	0.88 (0.85, 0.92)

Black Females Ages 18 to 35

From/To	*Underweight*	*Normal Weight*	*Overweight*	*Obese*
Underweight	0.45 (0.35,0.56)	0.47 (0.38,0.55)	0.07 (0.05,0.08)	0.01 (0.008,0.01)
Normal Weight	0.007 (0.003,0.01)	0.76(0.74, 0.78)	0.19 (0.17, 0.21)	0.04 (0.04, 0.05)
Overweight	0.0006 (0.0003,0.001)	0.12 (0.1, 0.14)	0.60 (0.57, 0.62)	0.29(0.26, 0.31)
Obese	0.00002 (0.00001, 0.00005)	0.007 (0.005, 0.01)	0.07 (0.06, 0.09)	0.92 (0.90, 0.94)

White Females Ages 18 to 35

From/To	*Underweight*	*Normal Weight*	*Overweight*	*Obese*
Underweight	0.25 (0.16,0.35)	0.69 (0.60,0.77)	0.055 (0.04,0.07)	0.006 (0.004,0.007)
Normal Weight	0.02 (0.01,0.02)	0.86 (0.85, 0.87)	0.11 (0.09, 0.12)	0.02 (0.01, 0.02)
Overweight	0.003 (0.002,0.004)	0.20 (0.17, 0.23)	0.60 (0.56, 0.64)	0.20 (0.17, 0.23)
Obese	0.0002 (0.00009,0.0002)	0.02 (0.01, 0.02)	0.11 (0.08, 0.14)	0.87 (0.84, 0.91)

Black Males Ages 36 to 45 (CARDIA)

From/To	*Underweight*	*Normal Weight*	*Overweight*	*Obese*
Underweight	0	0	0	0
Normal Weight	0	0.80 (0.75, 0.85)	0.18 (0.14, 0.23)	0.01 (0.01, 0.02)
Overweight	0	0.09 (0.06, 0.11)	0.79 (0.75, 0.82)	0.13 (0.10, 0.16)
Obese	0	0.004 (0.002, 0.01)	0.05 (0.03, 0.07)	0.95 (0.92, 0.97)

White Males Ages 36 to 45 (CARDIA)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.82 (0.79, 0.85)	0.17 (0.14, 0.20)	0.01 (0.008, 0.01)
Overweight	0	0.04 (0.03, 0.06)	0.85 (0.82, 0.87)	0.11 (0.09, 0.13)
Obese	0	0.003 (0.0007, 0.01)	0.06 (0.03, 0.09)	0.94 (0.91, 0.97)

Black Females Ages 36 to 45 (CARDIA)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.76 (0.71, 0.80)	0.21 (0.17, 0.25)	0.03 (0.02, 0.04)
Overweight	0	0.07 (0.04, 0.09)	0.72 (0.68, 0.76)	0.21 (0.18, 0.25)
Obese	0	0.003 (0.002, 0.007)	0.05 (0.04, 0.07)	0.94 (0.93, 0.96)

White Females Ages 36 to 45

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.88 (0.86, 0.90)	0.11 (0.09, 0.13)	0.01 (0.008, 0.01)
Overweight	0	0.07 (0.05, 0.10)	0.77 (0.73, 0.81)	0.16 (0.12, 0.19)
Obese	0	0.03 (0.01, 0.05)	0.04 (0.02, 0.06)	0.93 (0.90, 0.96)

Black Males Ages 46 to 55 (CARDIA)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.80 (0.70, 0.89)	0.19 (0.10, 0.29)	0.009 (0.004, 0.02)
Overweight	0	0.06 (0.02, 0.11)	0.85 (0.80, 0.91)	0.09 (0.04, 0.13)
Obese	0	0.006 (0.0003, 0.02)	0.03 (0.006, 0.05)	0.97 (0.94, 0.99)

White Males Ages 46 to 55 (CARDIA)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.86 (0.81, 0.91)	0.13 (0.08, 0.18)	0.008 (0.005, 0.01)
Overweight	0	0.053 (0.03, 0.08)	0.84 (0.80, 0.88)	0.10 (0.07, 0.14)
Obese	0	0.01 (0.0008, 0.03)	0.05 (0.02, 0.08)	0.94 (0.91, 0.97)

Black Females Ages 46 to 55 (CARDIA)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.73 (0.63, 0.82)	0.23 (0.15, 0.30)	0.04 (0.03, 0.07)
Overweight	0	0.07 (0.03, 0.11)	0.67 (0.60, 0.75)	0.26 (0.19, 0.34)
Obese	0	0.004 (0.0009, 0.01)	0.04 (0.02, 0.06)	0.96 (0.94, 0.98)

White Females Ages 46 to 55 (CARDIA)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0	0	0	0
Normal Weight	0	0.90 (0.87, 0.93)	0.09 (0.06, 0.12)	0.009 (0.006, 0.013)
Overweight	0	0.11 (0.07, 0.15)	0.74 (0.68, 0.79)	0.15 (0.12, 0.20)
Obese	0	0.004 (0.001, 0.01)	0.05 (0.02, 0.073)	0.95 (0.92, 0.97)

White Females Ages 46 to 55 (ARIC)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.50(.33, .68)	0.45(0.29,0.59)	0.05(0.03,0.07)	0.003(0.002,0.005)
Normal Weight	0.006(0.003,0.01)	0.81 (0.79, 0.83)	0.17 (0.15, 0.19)	0.02 (0.01, 0.02)
Overweight	0.0003(0.0001,0.0005)	0.08 (0.07, 0.10)	0.76 (0.73, 0.78)	0.16 (0.14, 0.17)
Obese	0.00002(0.000008,0.00006)	0.008 (0.004, 0.01)	0.07 (0.05, 0.08)	0.93 (0.91, 0.94)

White Males Ages 46 to 55 (ARIC)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.41(0.01,0.85)	0.45(0.006,0.77)	0.14(0.02,0.45)	0.008(0.002,0.02)
Normal Weight	0.001(0.0000,0.004)	0.78 (0.75, 0.81)	0.20 (0.18, 0.23)	0.04 (0.03, 0.04)
Overweight	0.0006(0.0000,0.0019)	0.07 (0.05, 0.08)	0.82 (0.80, 0.84)	0.19 (0.16, 0.23)
Obese	0.00004(0.0000,0.0001)	0.004 (0.003, 0.005)	0.10 (0.08, 0.12)	0.95 (0.93, 0.96)

Black Females Ages 46 to 55 (ARIC)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.50(0.18,0.88)	0.40(0.09,0.64)	0.09(0.02,0.17)	0.008(0.002,0.02)
Normal Weight	0.03(0.01,0.05)	0.66 (0.60, 0.72)	0.28 (0.23, 0.33)	0.04 (0.03, 0.04)
Overweight	0.003(0.0006,0.007)	0.06 (0.04, 0.09)	0.74 (0.70, 0.78)	0.19 (0.16, 0.23)
Obese	0.00008(0.00002,0.0003)	0.003 (0.001, 0.006)	0.05 (0.03, 0.06)	0.95 (0.93, 0.96)

Black Males Ages 46 to 55 (ARIC)

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.64(0.04,1)	0.32(0,0.81)	0.04(0,0.15)	0.002(0,0.009)
Normal Weight	0.004(0,0.01)	0.79 (0.73, 0.83)	0.19 (0.15, 0.24)	0.02 (0.01, 0.02)
Overweight	0.002(0,0.007)	0.07 (0.05, 0.10)	0.80 (0.76, 0.84)	0.13 (0.10, 0.16)
Obese	0.0002(0,0.0006)	0.005 (0.003, 0.008)	0.11 (0.08, 0.15)	0.88 (0.84, 0.92)

White Females Ages 56 to 64

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.53(0.04,1)	0.41(0,0.81)	0.05(0.03,0.07)	0.003(0.002,0.004)
Normal Weight	0.005(0.001756,0.0098036)	0.81 (0.79, 0.82)	0.17 (0.15, 0.19)	0.01 (0.01, 0.02)
Overweight	0.0003(0.00009,0.0005)	0.09 (0.07, 0.10)	0.77 (0.75, 0.79)	0.14 (0.12, 0.15)
Obese	0.0007(0.000004,0.003)	0.005 (0.003,0.007)	0.08 (0.06, 0.09)	0.92 (0.90, 0.93)

White Males Ages 56 to 64

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.53(0.04,1)	0.41(0,0.81)	0.05(0,0.14)	0.002(0,0.007)
Normal Weight	0.005(0.002,0.01)	0.79 (0.77, 0.82)	0.19 (0.17, 0.21)	0.01 (0.001, 0.01)
Overweight	0.0003(0.00009,0.0005)	0.06 (0.05, 0.07)	0.83 (0.81, 0.84)	0.11 (0.10, 0.12)
Obese	0.0007(0.000004,0.003)	0.004 (0.003, 0.006)	0.10 (0.09, 0.12)	0.89 (0.87, 0.91)

Black Females Ages 56 to 64

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	1	0	0	0
Normal Weight	0.01(0,0.03)	0.75 (0.67, 0.81)	0.22 (0.16, 0.28)	0.03 (0.02, 0.04)
Overweight	0.0004(0,0.001)	0.07 (0.04, 0.09)	0.73 (0.70, 0.77)	0.20 (0.16, 0.24)
Obese	0.00002(0,0.00006)	0.003 (0.002, 0.007)	0.07 (0.05, 0.09)	0.93 (0.91, 0.95)

Black Males Ages 56 to 64

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	1	0	0	0
Normal Weight	0.005(0,0.01)	0.79 (0.74, 0.85)	0.19 (0.13, 0.24)	0.02 (0.01, 0.0.02)
Overweight	0.0003(0,0.0009)	0.09 (0.06, 0.12)	0.77 (0.73, 0.81)	0.14 (0.11, 0.18)
Obese	0.00002(0,0.00009)	0.008 (0.005, 0.02)	0.12 (0.08, 0.16)	0.87 (0.28, 0.91)

White Females Ages 65 to 75

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.65(0.40,0.89)	0.31(0.10,0.54)	0.032(0.01,0.06)	0.002(0.0004,0.003)
Normal Weight	0.01(0.004,0.08)	0.82 (0.79, 0.85)	0.16 (0.13, 0.18)	0.01 (0.008, 0.01)
Overweight	0.0007(0.0003,0.001)	0.11 (0.08, 0.13)	0.78 (0.75, 0.81)	0.11 (0.09, 0.14)
Obese	0.00003(0.00001,0.00006)	0.007 (0.005, 0.009)	0.09 (0.07, 0.12)	0.90 (0.87, 0.93)

White Males Ages 65 to 75

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.42(0.01,1)	0.39(0,0.83)	0.17(0,0.61)	0.01(0,0.05)
Normal Weight	0.004(0,0.01)	0.84 (0.80, 0.87)	0.15 (0.12, 0.18)	0.009 (0.006, 0.01)
Overweight	0.0009(0,0.003)	0.07 (0.06, 0.09)	0.83 (0.81, 0.85)	0.10 (0.08, 0.12)
Obese	0.00006(0,0.0003)	0.005 (0.003, 0.007)	0.11 (0.08, 0.14)	0.89 (0.85, 0.92)

Black Females Ages 65 to 75

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.50(0.03,1)	0.43(0,0.81)	0.06(0,0.19)	0.004(0,0.02)
Normal Weight	0.03(0,0.07)	0.74 (0.63, 0.84)	0.21 (0.12, 0.31)	0.02 (0.007, 0.04)
Overweight	0.003(0,0.008)	0.12 (0.08, 0.18)	0.77 (0.71, 0.84)	0.10 (0.06, 0.15)
Obese	0.0001(0,0.0005)	0.009 (0.005, 0.02)	0.10 (0.059, 0.13)	0.90 (0.85, 0.93)

Black Males Ages 65 to 75

From/To	Underweight	Normal Weight	Overweight	Obese
Underweight	0.65(0.09,1)	0.0008(0,0.003)	0.03(0,0.10)	0.32(0,0.83)
Normal Weight	0.02(0,0.05)	0.89 (0.83, 0.95)	0.09 (0.04, 0.15)	0.007 (0.001, 0.02)
Overweight	0.001(0,0.003)	0.07 (0.03, 0.11)	0.85 (0.79, 0.91)	0.07 (0.03, 0.12)
Obese	0.01(0,0.035)	0.006 (0.002, 0.01)	0.14 (0.07, 0.22)	0.85 (0.77, 0.92)

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