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Projection of US adult obesity trends based on individual BMI trajectories

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ABSTRACT

Adult obesity has been increasing in the United States since the 1980s. For the cohorts now in young adulthood, the future prevalence of obesity depends on current prevalence and future increase in weight. In order to investigate the future of obesity, we pooled 92,615 body-mass index (BMI) measures from 26,337 adults interviewed and examined by the National Health and Nutrition Examination Survey (NHANES), aged between 25 and 55 in years 1998-2018. We applied functional data analysis to probabilistically reconstruct individual BMI trajectories. We found that the prevalence of obesity at age 55 is expected to reach 58% (95% uncertainty interval [UI], 54%-61%) for females born in 1984-1988 and 57% (95% UI, 53%-61%) for males born in the same cohort. The prevalence of severe obesity at age 55 will increase rapidly in both sexes. Time spent being obese will increase, e.g. for females from 10.7 years (95% UI, 10.4–10.9 years) in the 1964-68 cohort to 14.7 years (95% UI, 14.2-15.3 years) in the 1984-88 birth cohort. Although obesity prevalence may level off in the coming decades, higher prevalence of severe obesity as well as longer durations of obesity are therefore expected to increase the burden of this disease.

KEYWORDS: projections**,** obesity, time spent obese, BMI trajectory reconstruction

Introduction

The prevalence of obesity, defined as body mass index (BMI, weight / height^2) above 30kg/m^2, has been rising steeply among adults (aged ≥ 20) in the United States since the 1980s, from 15% in 1976-1980 to 42.5% in 2017-1018 [1, 2]. Obesity is a risk factor for many major chronic diseases, notably type 2 diabetes,[3] cardiovascular diseases [4, 5] and for some types of cancers [6]. Accordingly, obesity is associated with all-cause mortality [7, 8]. Obesity has been one of the most important contributors to slow health improvements in the United States in recent decades [9] and is expected to continue exert a strong influence on US life expectancy [10, 11]. Although BMI at the time of survey is the most accessible and, therefore, the most widely used summary of an individual's weight history, it is likely that the effects of obesity on an individual's health are cumulative. For this reason, other characteristics of BMI trajectories have also been investigated. It has, for example, been shown that duration of obesity [12] maximum BMI ever attained [13] and weight change [14] are associated with changes in the risk of death.

Making accurate predictions of trends in several obesity metrics is crucial to assessing the future burden of the obesity epidemic. This goal can only be achieved by using information already available on obesity prevalence in younger birth cohorts, and reasonable assumptions about its future evolution. The most common approach to obesity projection has been the extrapolation of prevalence based on past trends [15-17]. However, this approach does not recognize the fact that obesity may have a strong cohort component, as at the individual level weight at a given age determines his or her weight at any subsequent age. In other words, BMI is highly correlated over the life course. Integrating already observed cohort histories of obesity is therefore key to increasing the accuracy of projections. Other projection methods have taken into account the cohort effect in obesity, but have discretized information on BMI into classes prior to projection [11]. This results in a loss of information and in potentially biased estimates. For example, future obesity prevalence may depend on whether mean BMI among currently overweight individuals is closer to normal (25 kg/m^2) or to obese (30 kg/m^2). Moreover, an important assumption of the methods that account for cohort effects has been the Markov property: the probability of being obese at a future point in time is assumed to depend only on current status. In reality, the trajectory up to the current observation may carry useful information. Finally, analyses that account for BMI histories have relied on reported past weights without investigating recall bias [9, 11, 13].

A recent study by Ward et al. incorporated individual-level BMI data to construct projections for children [18]. Using a “stitching” procedure on individual-level data pertaining to past cohorts to establish the heterogeneity in BMI trajectories in children followed by quantile regressions and calibration of individual-level trajectories against population-level trends, these authors built a simulation model of the risk of obesity at age 35. This approach indicated that 57.3% of today’s US children are expected to be obese at this age.

The present study develops a method of projection that, like Ward et al., builds on the fact that an individual’s BMI is a function of age, and can indeed be treated as such. By contrast, the proposed Bayesian hierarchical model probabilistically reconstructs an individual’s BMI trajectory based on knowledge of its reporting error-corrected value at specific ages, and on observations of common patterns across individuals. Thus, for any birth cohort, the method both preserves the available information (the part of the BMI trajectory that has already been observed) and utilizes information collected on earlier cohorts, who were observed to older ages. The approach accounts for changes in the population distribution when estimating total population patterns; corrects for self-reporting bias; allows past history to influence the future, thereby removing the common Markov assumption on obesity projections; and enables the simultaneous projection of any BMI metric of interest. We investigated four among the cohorts born between 1943 and 1993: the prevalence of obesity and severe obesity at age 55, and the time spent being obese and being severely obese between ages 25 and 55.

Methods

Data source

We use data from the National Health and Nutrition Examination Survey (NHANES), which is a series of nationally representative surveys of the US civilian non-institutionalized population conducted by the National Center for Health Statistics [19]. The surveys include a physical examination by trained technicians in a mobile examination center, during which the height and the weight of participants are measured. During a home interview, participants are asked to report their current weight, as well as their weight one year before the survey (if aged 16 or older), 10 years before the survey (if aged 36 or above), and at age 25 (if aged 27 or older). The data have been collected on a continuous basis since 1999 (continuous NHANES), and are released in two-year cycles. We pooled all of the available cycles of continuous NHANES (1999-2018). The dataset analyzed included all of the participants examined between ages 25 and 55, with no missing data on education or smoking status at age 25 (N = 26,337).

Correction for misreporting of past weights

It is well-known that height and weight are often misreported [20-22]. We therefore computed all of the BMIs using the individual's measured height, and used the individual's measured weight for the current BMI. We first computed past BMIs using reported weights. We then corrected each individual's past BMIs by adding to them the difference between the current measured BMI and the reported BMIs. Of note, this correction is participant-specific and quantitatively more important for obese participants, who tend to under report more their current weight. We then added an age-, cohort-, and sex-specific corrective term matching the mean of corrected past BMIs to means of values measured at previous NHANES cycles. A detailed description of the procedure is given in the eMethods.

Functional data analysis

Since we expected weight gain over time to differ between these groups, we defined strata based on sex, race/ethnicity (non-Hispanic Black, non-Hispanic White, Hispanic, other race), educational attainment (high school or less, some college, college graduate), and smoking status at age 25 (smoker/non-smoker). The aggregation of stratum-specific projections allowed us to account for the changes in the population distribution in national-level projections.

In each stratum, we applied a recently developed Bayesian hierarchical model for the smoothing of functional data [23]. The method assumes that within each stratum, individual BMI trajectories are independent realizations of a Gaussian process measured with independent normally distributed errors. A Gaussian process prior is set for the mean function, and an Inverse-Wishart process prior is set for the covariance function of the Gaussian process.

To obtain unbiased national projections, for each individual i in the sample, the posterior distribution of the Gaussian process for i is taken as the expected value of the BMI trajectory of the w_i individuals, who are represented by individual i in the sample (where w_i is i's NHANES examination weight).

Obesity metrics considered

We considered four obesity metrics: the prevalence of obesity at age 55 (BMI > 30 kg/m^2), the prevalence of severe obesity at age 55 (BMI > 40 kg/m^2), the time spent being obese between ages 25 and 55, and the time spent being severely obese between ages 25 and 55.

Sensitivity analyses

We repeated the projection exercise with the older, low-obesity prevalence cohorts (born in 1943-1954) removed from the dataset in order to check their influence on our projections.

Curve reconstruction was performed using the MATLAB toolbox BFDA [24]. All other analyses were conducted using R [25]. NHANES data are freely available at https://wwwn.cdc.gov/nchs/nhanes/. All computer codes used to generate the results reported in this study will be posted in an open archive upon publication.

Results

Characteristics of participants analyzed

Table 1 presents summary characteristics of the N=26,337 participants analyzed. A simple comparison of the proportions currently obese and obese at age 25 in the sample serves to illustrate the importance of weight gain in adulthood. The continuation of smoking was found to be highly predicted by smoking at age 25, our measure of smoking status (eFigure 3). Expected historical trends were observed in the composition of the birth cohorts analyzed: e.g., declining prevalence of smoking, increasing size of the Hispanic group, and rising educational attainment among females (eFigures 4-6).

Individual-level trajectories between ages 25 and 55

Figure 1A plots the BMI curves of selected members of the same stratum, but who were interviewed by NHANES at different ages. The figure shows that while the reconstruction of an individual's BMI trajectory uses information specific to that trajectory, it is also informed by the trajectories of the other members of the same stratum, and, in particular, of those who were observed to the oldest age considered, namely age 55.

Average BMI trajectory between ages 25 and 55

Examples of group-level age trends (posterior distribution of the Gaussian process mean function) are shown in Figure 1B for the eight selected strata, that of non-smokers with the lowest educational attainment. Although starting with similar values of mean BMI at age 25, weight gain with age was found accelerated among non-Hispanic Black women compared to non-Hispanic White and Hispanic women (Figure 1B, left panel). By contrast, little evidence could be found that the pace of weight gain varied by race/ethnicity in men (Figure 1B, right panel). Among both males and females, the “other race” group, that includes Asian Americans, showed markedly lower mean BMI values across the age span investigated. See eFigure 7 in the Supplement for results on all strata.

Obesity prevalence at age 55

Obesity prevalence at age 55 will continue to increase, and is predicted to cross the 50% line in both males and females (Figure 2, top panels). In females, it is 46.6% (95% uncertainty interval [UI], 44.4 % - 48.8%) for the cohort currently aged 55 (the 1959-1963 birth cohort), but it is expected to reach 57.5% (95% UI, 53.8% - 61.2%) for those born in 1984-1988. The predicted plateauing of female obesity prevalence at age 55 for the younger cohorts (born after 1980) echoes the plateauing of obesity prevalence already observed at younger ages in these cohorts (eFigure 8) and was also observed when older cohorts were removed from the analysis (eFigure 9). The model predicts that 57.4% (95% UI, 53.3% - 61.4%) of men of the 1984-1988 birth cohort will be obese at age 55.

Large differences were found in the projection by race/ethnicity (Figure 3). For instance, for the 1979-1983 birth cohort, obesity prevalence at age 55 is expected to reach 78.2% (95% UI, 72.2% - 83.7%) among non-Hispanic Black women, but just 53.6% (95% UI, 48.9% - 58.1%) among non-Hispanic White women.

Severe obesity prevalence at age 55

The model predicts that severe obesity at age 55 will increase rapidly among females, from 9.0% (95% UI, 7.8% - 10.3%) in the 1959-1963 to 16.0% (95% UI, 13.5% - 18.6%) for those born in 1984-88 (Figure 2, lower panels). Similarly, among males, severe obesity at age 55 will increase over the next two decades, from its current value of 5.3 % (95% UI, 4.5% – 6.2%) to 12.1% (95% UI, 9.8% – 14.7%) for the 1984-88 birth cohort.

Time spent being obese by age 55

The time spent being obese between ages 25 and 55 is expected to increase rapidly over the next two decades among both males and females (Figure 4, upper panels). On average, a woman of the 1984-88 birth cohort is expected to spend 14.7 years (95% UI, 14.2-15.3 years) being obese between ages 25 and 55, while the corresponding figure for a woman of the 1964-68 cohort was 10.7 years (95% UI, 10.4 – 10.9 years). These findings reflect both the increased prevalence of obesity and the longer durations of obesity for obese individuals. Indeed, in the same cohort (females born in 1984-88), the average time spent being obese between ages 25 and 55 by those who are obese at age 55 is expected to reach 22.8 years (95% UI, 22.0 – 23.6 years), compared to 19.1 years (95% UI, 18.4 – 19.7 years) for the 1964-68 cohort. The same pattern was observed for severe obesity in both sexes, with an expected steep increase in time spent above 40 kg/m^2 for young adult cohorts (Figure 4, lower panels).

Discussion

After increasing for several years, obesity prevalence at age 55 is expected to level off in the coming decades. This projection is in line with recent reports that obesity prevalence is starting to stabilize in younger age groups [26, 27]. The examination of metrics other than obesity prevalence reveals more worrisome developments, since the prevalence of severe obesity at age 55 and the time spent being obese in adulthood are expected to increase more steeply in the coming decades.

In addition, there is considerable heterogeneity in the level at which the stabilization is expected to occur, in particular with respect to race/ethnicity. This heterogeneity is especially visible in females, as we predict that for the cohorts who are now in their twenties, half of non-Hispanic White women, but four out five non-Hispanic Black women, will be obese at age 55.

Our estimation of future obesity prevalence seems somewhat more optimistic than others that have recently been published: while we expect that 59.6% (females) and 51.3% (males) of the 1989-1993 birth cohort will be obese at age 55, Ward and coauthors predicted that 57.3% of today's children (aged 19 or younger) will already be obese at age 35. This discrepancy might be due in part to a true intensification of obesity between the cohorts who are currently in young adulthood and those who are still in childhood or adolescence. Another potential explanation is that the linear quantile regression of weights on calendar time treats distant and recent changes in weight quantiles as equally informative regarding future trends, which makes it difficult to capture plateau-like phenomena. Indeed, linear regression predicts some quantiles of the BMI distribution that have not shown recent signs of evolution will increase in the future, simply because of increases that occurred prior to 2000. More recent work appears more in line with our estimates [28].

Because obesity will continue to be one of the most important determinants of health trends in the US in the near future, accurate estimation of its future magnitude is needed. Of particular relevance here is the fact that obesity is highly correlated across the life course: most of the information on future obesity of a birth cohort can be found in the current status of its members.

The approach that we propose has several distinct strengths. We have tackled the problem of misreporting of past weights and have directly addressed both the challenges and the opportunities presented by correlated weight status over the life course by applying a flexible functional data analysis technique that enables the full reconstruction of individual BMI trajectories. Our approach naturally implements two conditions that should be met when making obesity predictions. First, closely related health metrics such as obesity and severe obesity prevalence should not be projected using separate procedures. By feeding all of the available information for the reconstruction of BMI trajectories into a single, comprehensive Bayesian framework, we allow for the simultaneous projection of any quantity of interest in a single procedure. Second, recent observations should be given more weight than distant ones. If met, this condition notably translates into the fact that as we progressively move away from the present, uncertainty about the projected quantities increases. This is naturally the case with Gaussian processes, but not with simpler methods that make stronger assumptions. Among the other strengths of our approach are that by stratifying the projections, we account for changes in the population distribution when estimating total population patterns; and that the procedure allows history to influence the future, thereby removing the common Markov assumption on obesity projections.

We also acknowledge the limitations of our approach. We limit the reconstruction of the BMI trajectories to ages 25-55 in order to avoid selection due to rising mortality among older individuals. The projection horizon is therefore limited. A common metric such as obesity prevalence among all adults cannot be estimated without additional assumptions being made about the cohorts who are currently in childhood. In addition, we assume that individuals with identical observed BMI trajectories will follow similar BMI paths at older ages, irrespective of birth cohort.

In conclusion, we find that although the prevalence of obesity is expected to stop rising at the national level, there is an alarming degree of heterogeneity in the levels at which this is expected to occur. Moreover, the time spent being obese and the time spent being severely obese are expected to increase rapidly in the next two decades. Obesity duration is highly likely to be a crucial determinant for the increased susceptibility of obese people to late adulthood diseases such as type 2 diabetes. Our predictions for time spent obese therefore suggest a sharp increase in the prevalence of obesity-induced diseases will occur. An accurate assessment of the future burden of obesity requires us to move beyond the focus on obesity prevalence.

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Supplement to: Projection of US adult obesity trends based on individual BMI trajectories

Contents

eMethods. Correction for misreporting of past BMIs.

Current BMI and bias of current reported BMI

All BMIs were computed using measured height. For each individual, current BMI could be computed using either measured or reported weight (“measured BMI” and “reported BMI” for short). As expected from earlier studies, weight was found misreported in females, and hence reported BMI was found biased (Table S2, first column). For each individual, we used measured BMI for current BMI in subsequent curve reconstruction. For each individual, we also computed the difference between measured and reported current BMIs (current bias).

First correction of past BMIs

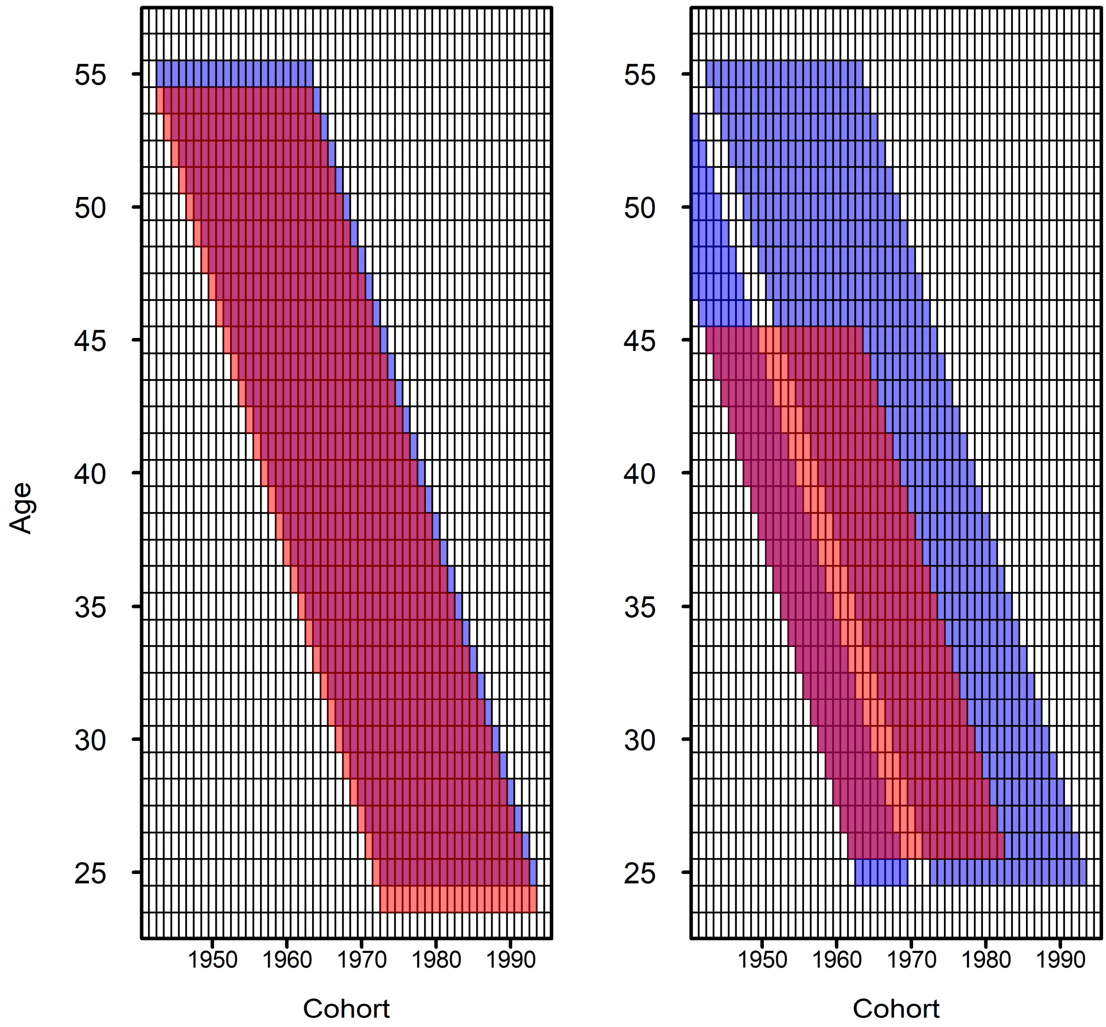
We began by computing past BMIs (1 year before survey, 10 years before survey, and at age 25) using past reported weights. We thereafter constructed a first set of corrected past BMIs by adding the aforementioned current bias to this first series of past BMIs. This first correction is therefore specific to each individual.

Second correction of past BMIs

To assess whether a bias existed for past BMIs even after the first correction, we compared (separately for males and females) age and cohort specific mean BMIs estimated using these corrected past BMIs and using BMIs measured during NHANES II (1976-1980), NHANES III (1988-1994) and continuous NHANES. For example, the average BMI of the 1960 birth cohort at age 30 years could be estimated using average BMI 10 years before survey as reported in 2000 by members of this birth cohort, but was also using BMI actually measured in 1990, during NHANES II. This enabled the assessment of a specific misreporting of past BMIs. The regions of the Cohort x Age plane in which average BMI could be estimated using measured BMIs and reported BMIs 1 and 10 years before survey are given on eFigure 1.

We found evidence for misreporting of past BMIs even after the first correction. Most notably, for women, the mean BMI surface estimated using BMI 10 years before survey was systematically below the surface estimated using measured BMIs (eFigure 2). For each sex, we therefore constructed a second set of BMIs 1 year and 10 years before survey by adding to the first set of corrected BMIs the age, cohort and sex specific difference between the two relevant surfaces. We proceeded in a similar fashion for BMI at 25.

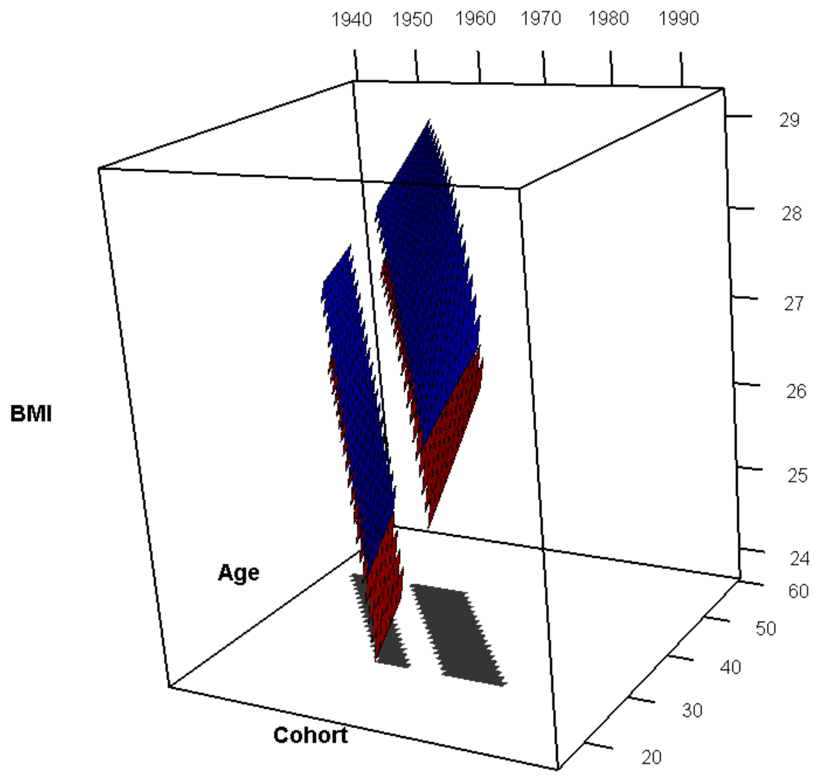
Corrections brought to past BMIs are summarized in eTable 2. The proportion of observations above 30 kg/m^2 for each BMI series (uncorrected, first correction, second correction) is given in eTable 3.



eFigure 1. Domains of the Cohort x Age plane where average BMI can be estimated using measured BMIs (blue) and reported past BMIs (red).

Left panel: the red region corresponds to reporting of BMI 1 year before survey.

Right panel: the red region corresponds to reporting of BMI 10 before survey. Reported BMIs can be compared with BMIs measured at both continuous NHANES (right-hand blue domain) and NHANES III (left-hand blue domain).



eFigure 2. Mean female BMI surface, estimated using either measured BMI (blue) or reported BMI 10 years before survey after first correction (red). In each case, the BMI surface was estimated with a Generalized Additive Model with a Gamma distribution, using survey weights for unbiasedness.

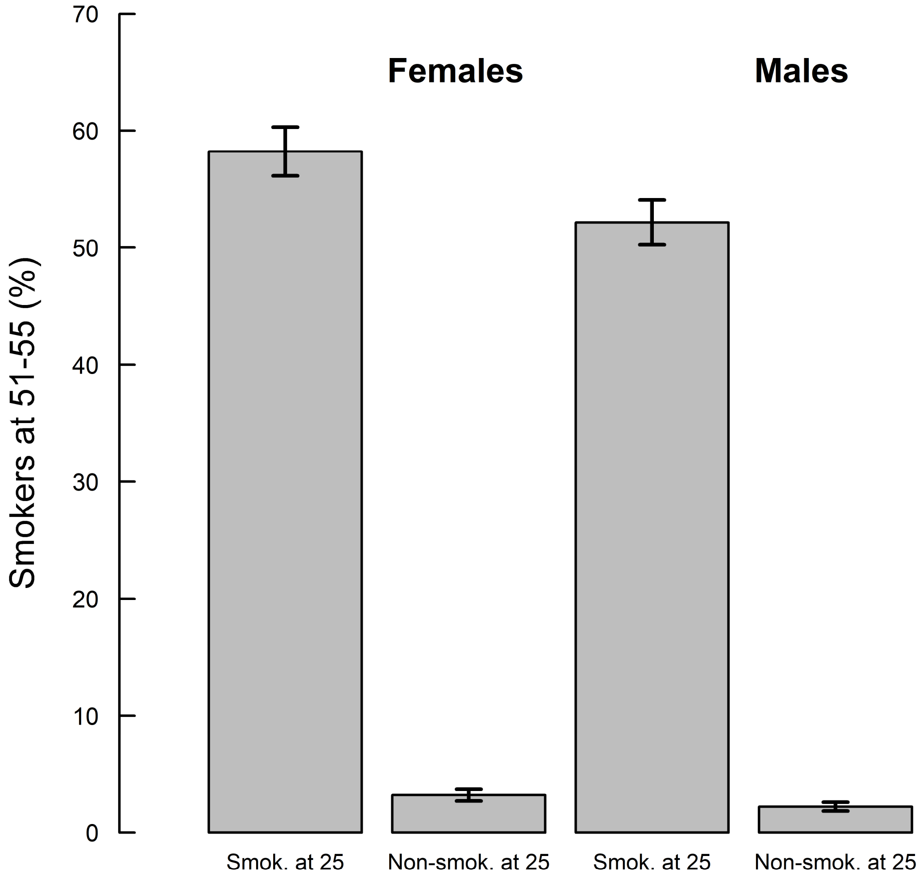
	Bias of current reported BMI	Global correction for BMI		
		1y before survey	10y before survey	at 25
Females	0.52 (1.70)	0.45 (1.68)	1.17 (1.68)	1.45 (1.72)
Males	0.04 (1.62)	-0.17 (1.61)	0.11 (1.52)	0.26 (1.56)

eTable 1. Mean (SD) bias of current reported BMI, and mean correction (SD) applied to reported past BMIs.

Data: All members of the final dataset analyzed (N=26,337).

	Uncorrected	First correction	Second correction
Current BMIs	35.1%	36.7%	-
BMIs 1y before survey	34.7%	36.2%	35.5%
BMIs 10y before survey	22.6%	24.5%	26.1%
BMIs at 25s	13.2%	15.0%	16.6%

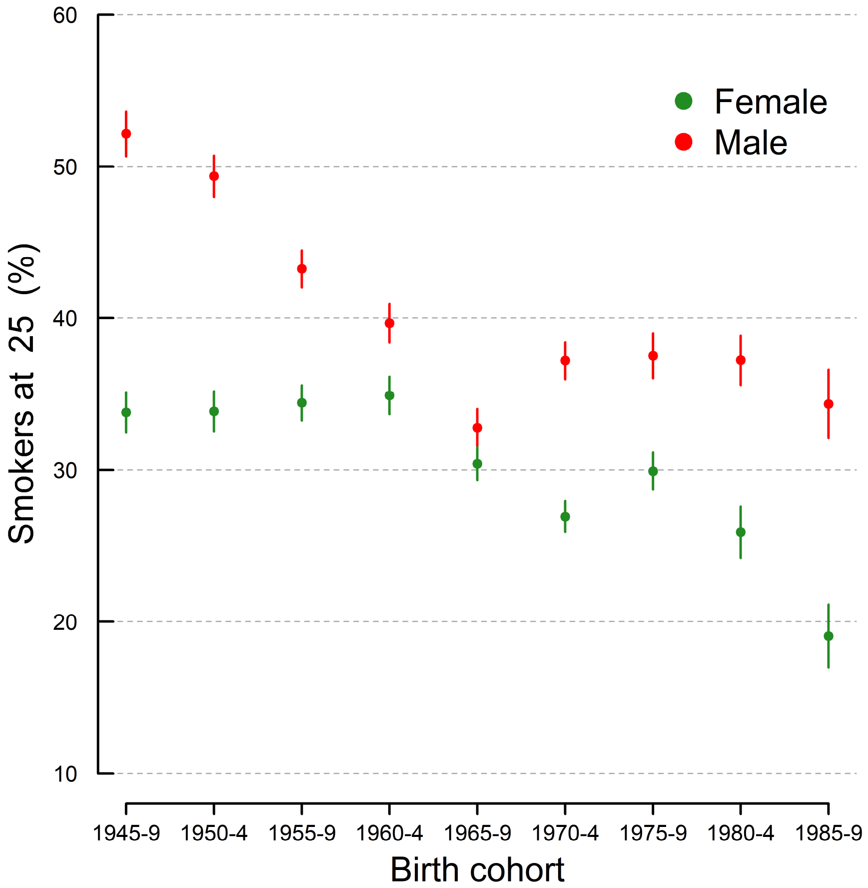
eTable 2. Proportion of data points in the 'obese' category (>30kg/m^2), for each series of BMIs (uncorrected, first correction, second correction).



eFigure 3. Probability of smoking at age 51-55 according to smoking status at age 25 and sex.

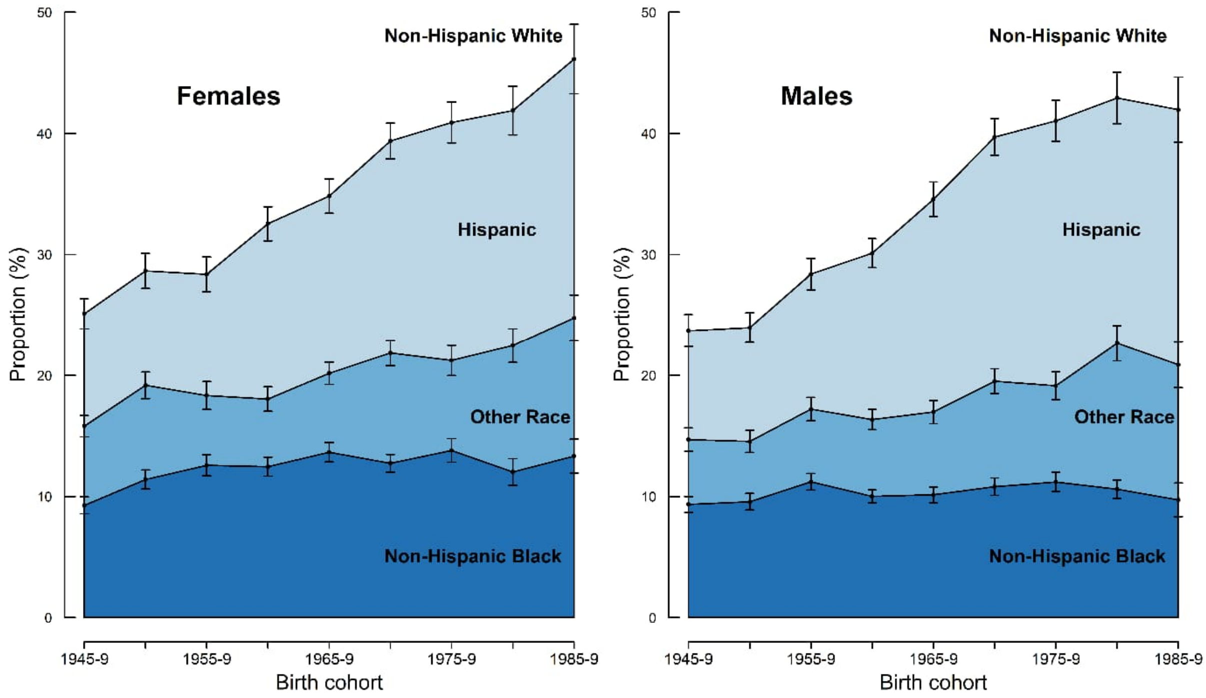
Data : individuals aged 51-55 at continuous NHANES interview.

Proportion ± standard error (s.e.).



eFigure 4. Proportion smoking at age 25, by birth cohort and sex.

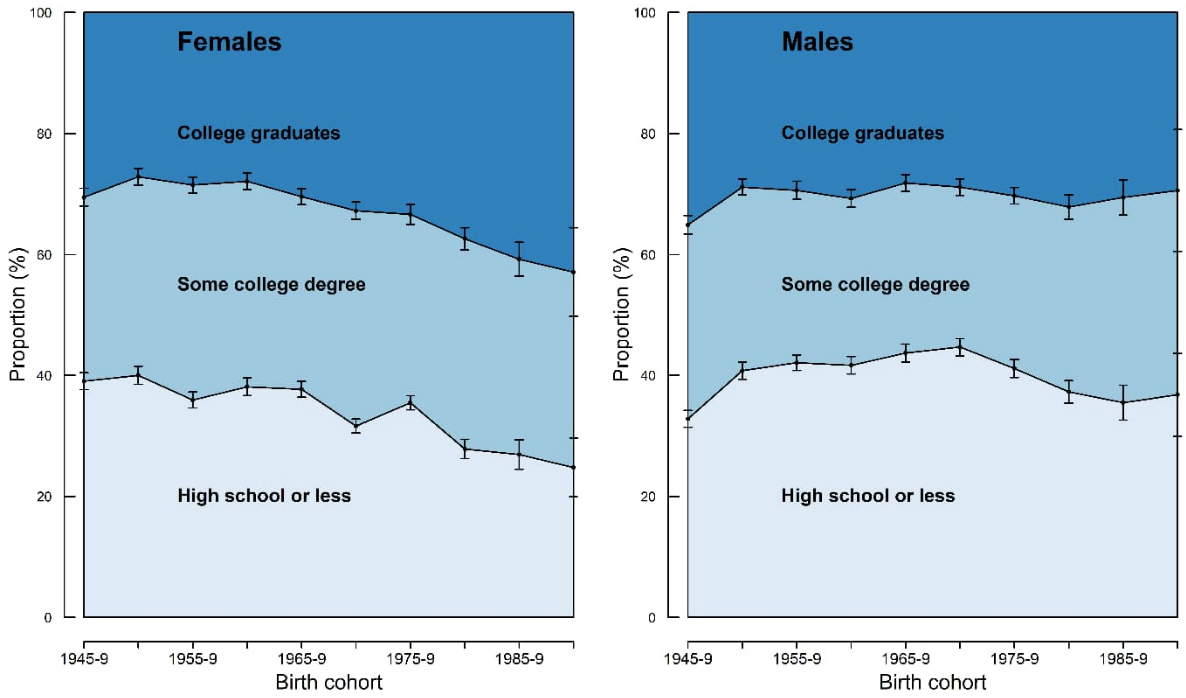
Proportions ± s.e.



eFigure 5. Ethnic composition of birth cohorts, by sex.

Data: individuals 25 years and older at NHANES interview.

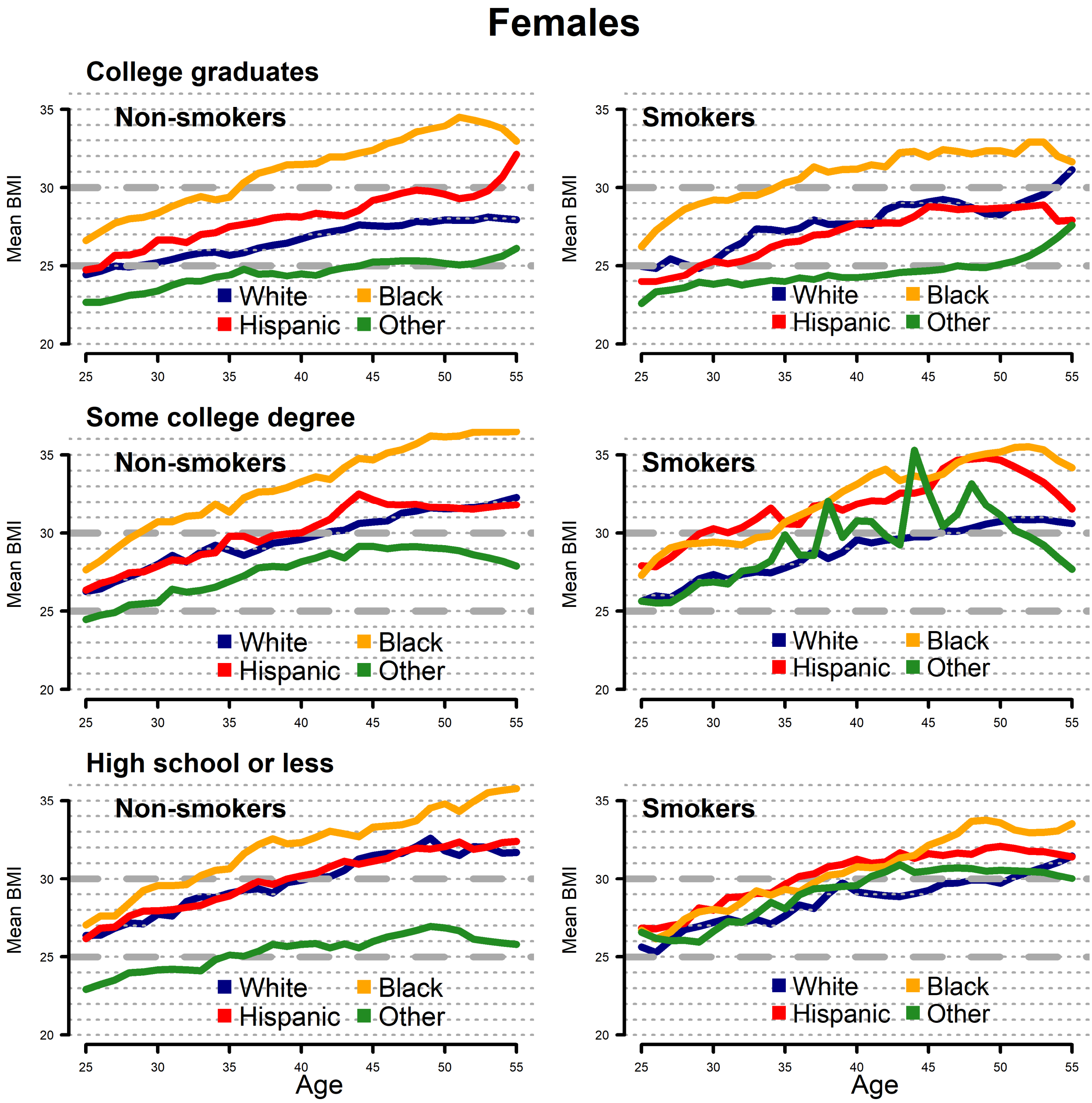
Proportions ± s.e.

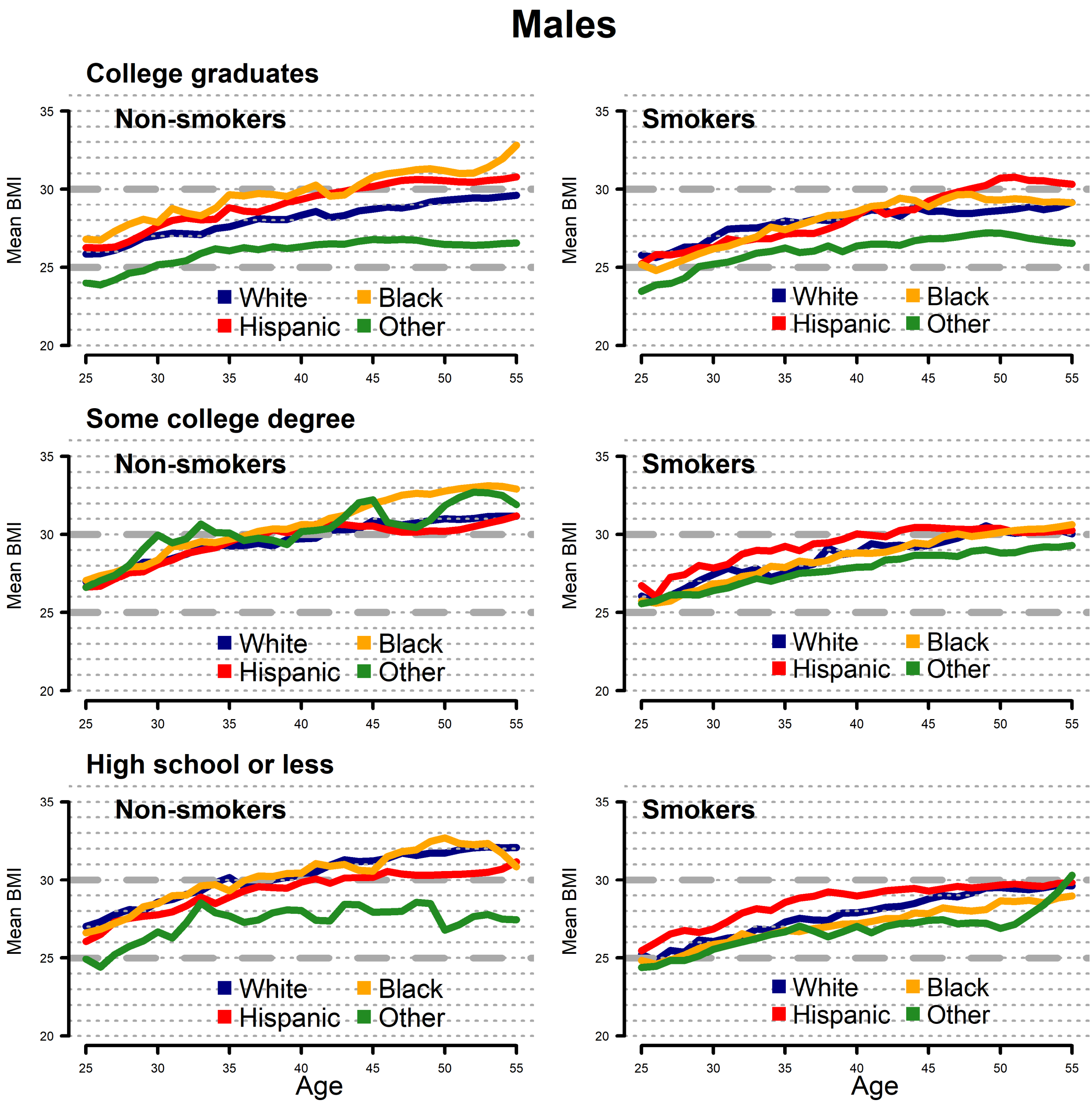


eFigure 6. Educational attainments by birth cohort and sex.

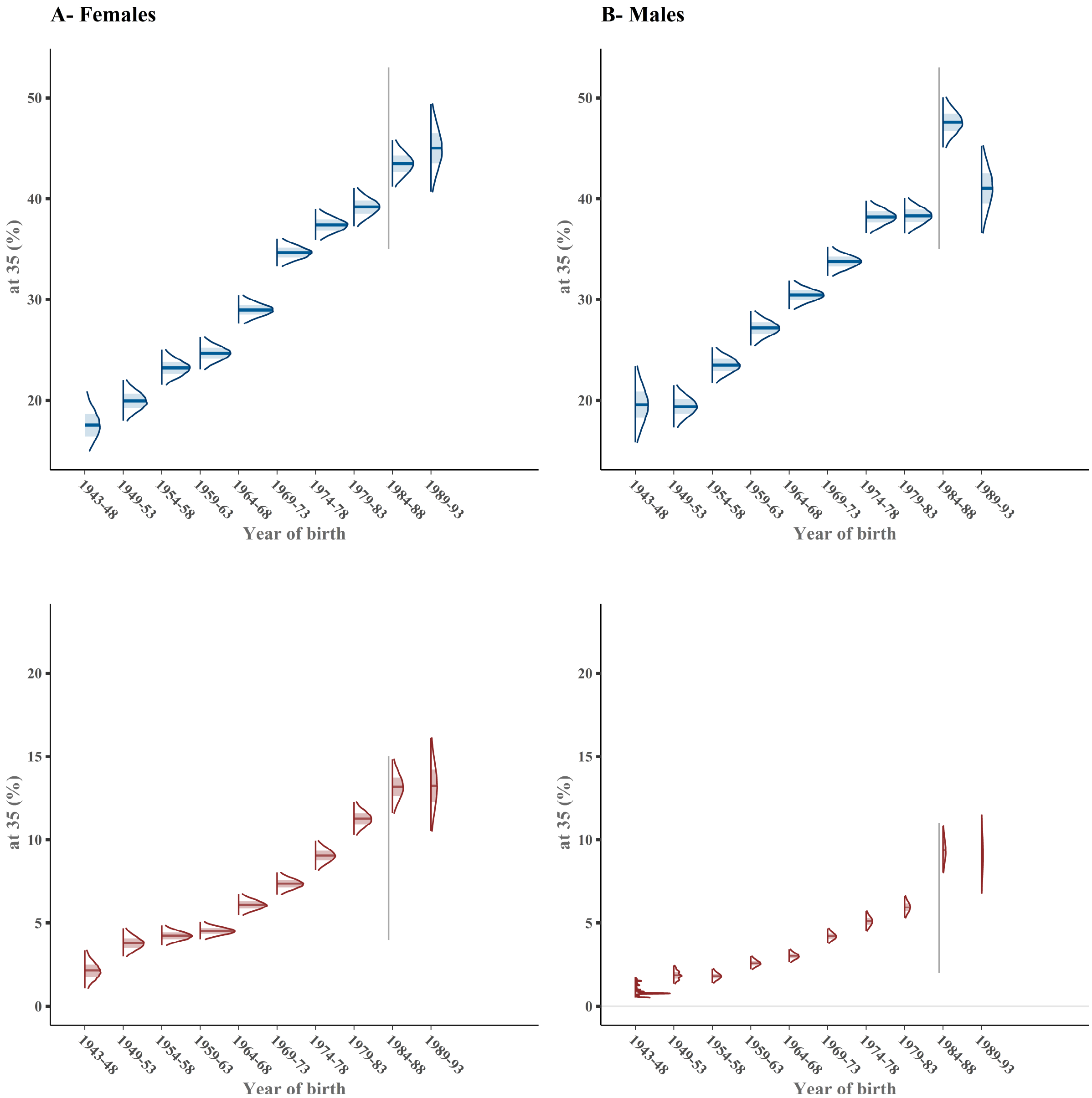
Data: individuals 25 years and older at NHANES interview.

Proportions ± s.e.


Females
College graduates
Non-smokers
Smokers
Some college degree
Non-smokers
Smokers
High school or less
Non-smokers
Smokers
Mean BMI
Age
White
Black
Hispanic
Other



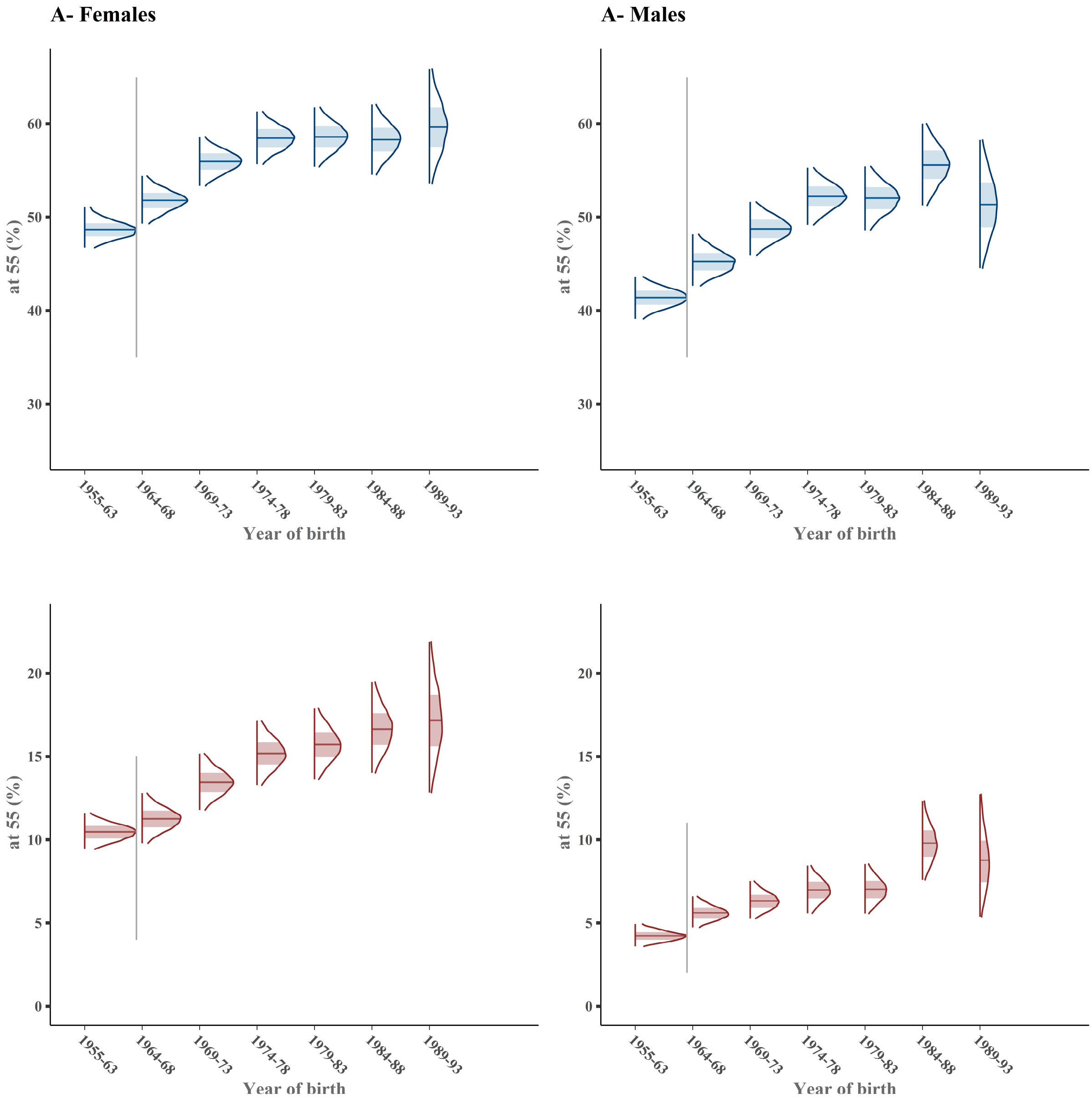
eFigure 7. Average posterior of the mean BMI function for strata defined by sex, race/ethnicity, educational attainment and smoking status at age 25.



eFigure 8. Obesity and severe obesity at age 35, by sex.

Top panels: obesity prevalence at age 35 by birth cohort, for females and males separately. Lower panels: severe obesity prevalence at age 35. On each plot, a vertical line separates retrospective estimates from 'true' projections.

The shaded regions are 50% UIs; the outer regions are 95% UIs.



eFigure 9. Obesity and severe obesity at age 55, by sex, with older cohorts (1943-54) removed from the dataset.

TABLES AND FIGURES

	Females N = 13,811	Males N = 12,526
Year of birth (mean, range)	1969 (1943-1993)	1968 (1943-1993)
Race		
Hispanic	3,747 (27.1%) [15.0%]	3,312 (26.4%) [16.1%]
Non-Hispanic Black	3,011 (21.8%) [12.9%]	2,625 (21.0%) [10.9%]
Non-Hispanic White	5,537 (40.1%) [64.3%]	5,226 (41.7%) [65.5%]
Other Race	1,516 (11.0%) [7.8%]	1,363 (10.9%) [7.5%]
Education		
High school or less	5,785 (41.9%) [35.1%]	6,115 (48.8%) [41.6%]
Some college	4,346 (31.5%) [32.6%]	3,398 (27.1%) [28.3%]
College graduates	3,680 (26.6%) [32.3%]	3,013 (24.1%) [29.5%]
Smokers at 25		
Yes	3,825 (27.7%) [30.7%]	5,050 (40.3%) [39.2%]
No	9,986 (72.3%) [69.3%]	7,476 (59.7%) [60.8%]
Currently obese		
Yes	5,364 (38.8%)	4,234 (33.8%)
No	8,271 (59.9%)	8,292 (66.2%)
Not available*	176 (1.3%)	0 (0.0%)
Obese at 25		
Yes	2,414 (17.5%)	2,009 (16.0%)
No	10,979 (79.5%)	10,156 (81.1%)
Not available	418 (3.0%)	361 (2.9%)
Number of observations (mean, SD)	3.5 (0.7)	3.5 (0.6)

Table 1. Characteristics of participants analyzed.

Percentages in parentheses are unweighted proportions; percentages in brackets are proportions weighted by sampling weights and therefore estimate the composition of the US population for the variables we stratify the analysis on.

*except at cycle A, pregnant women were asked to report their weight *before* pregnancy, which can be used in the present analysis as the current BMI (but with no individual-level correction); current weight of the N=169 pregnant women of cycle A was removed from the analysis, while there was non-response of N=s7 pregnant women interviewed at other cycles.

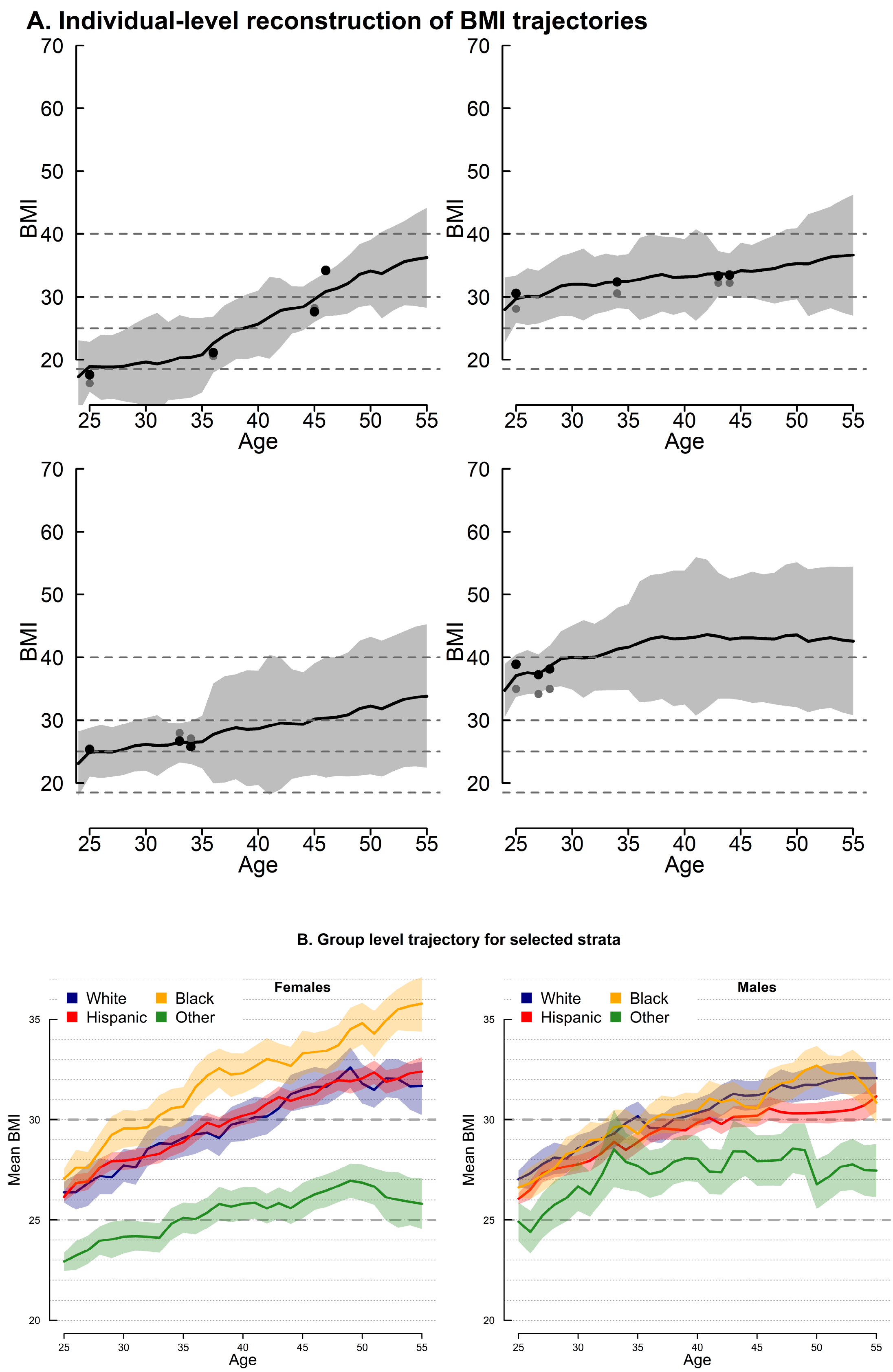


Figure 1A and 1B. Example reconstructions of BMI trajectories

Panel A shows examples of the BMI trajectories (average posterior and 95% uncertainty interval [UI]) of NHANES participants who all belong to the same stratum (that of Black non-smoking females with the lowest educational attainment). BMIs based on uncorrected reported weights are shown in gray. BMIs corrected for misreporting, which are used in the analysis, are shown in black. The reconstruction of the trajectory of individuals interviewed at younger ages (bottom plots) is informed by both the available information on their own BMI histories (e.g., normal or elevated BMI), as well as on the trajectories of older individuals (top plots). Once the BMI trajectory of an individual has been reconstructed, all metrics of interest, e.g., the probability of being above some threshold value or time spent above this threshold, can be computed.

Panel B shows the average posterior (with 95% UI) of the mean BMI function for non-smoking females (left) and males (right) with the lowest educational attainment (high school or less). See eFigure 7 in the Supplement for the average posterior of the mean BMI function for all strata.

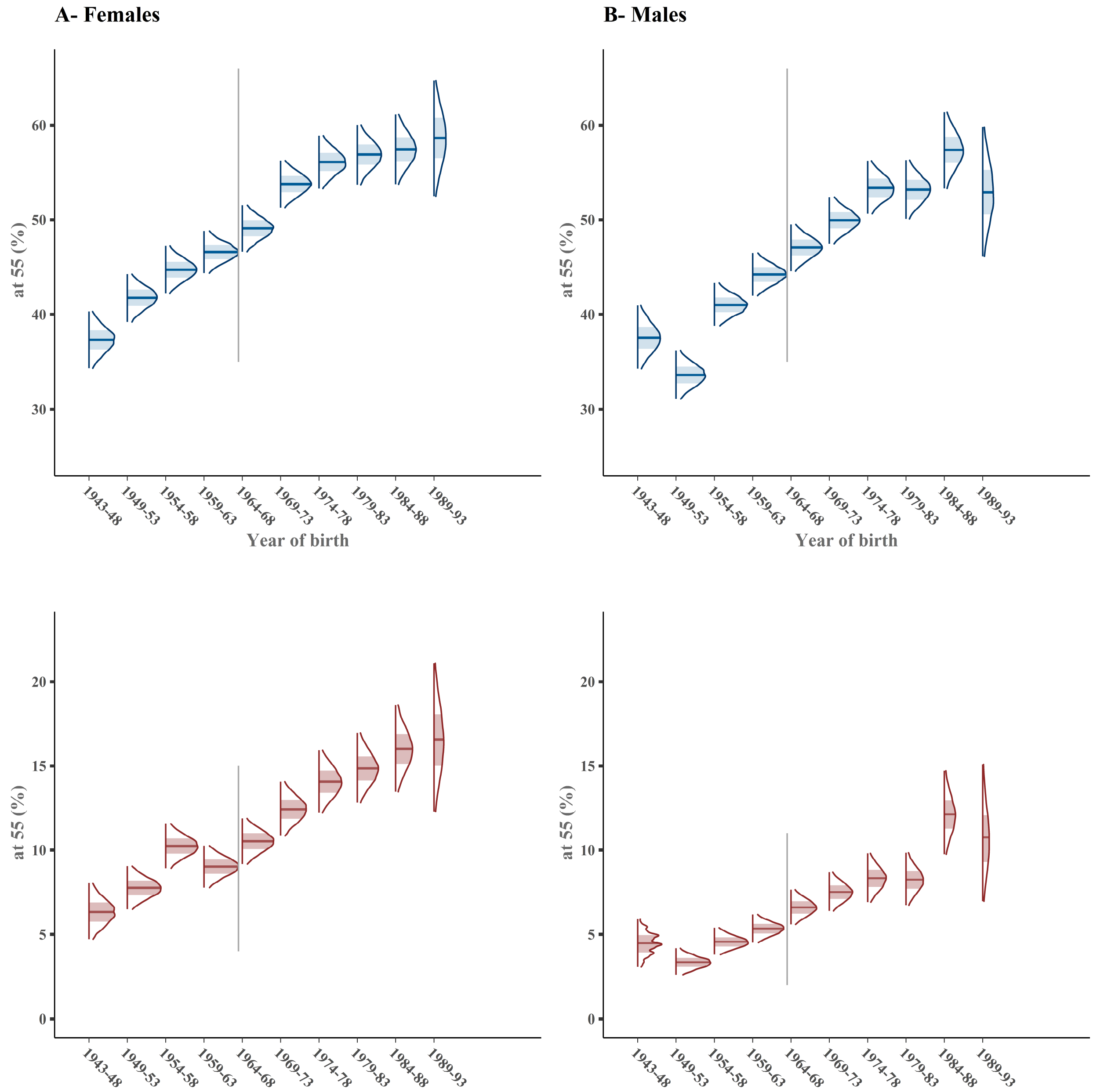


Figure 2. Projection of obesity and severe obesity at age 55, by sex.

The top panels show obesity prevalence at age 55 by birth cohort, for females and males separately; similarly, the lower panels show severe obesity (BMI > 40) prevalence at age 55. On each plot, a vertical line separates retrospective estimates (estimates for cohorts who have already attained age 55) from “true” projections (estimates for cohorts still below age 55). The shaded regions are 50% UIs; the outer regions are 95% UIs.

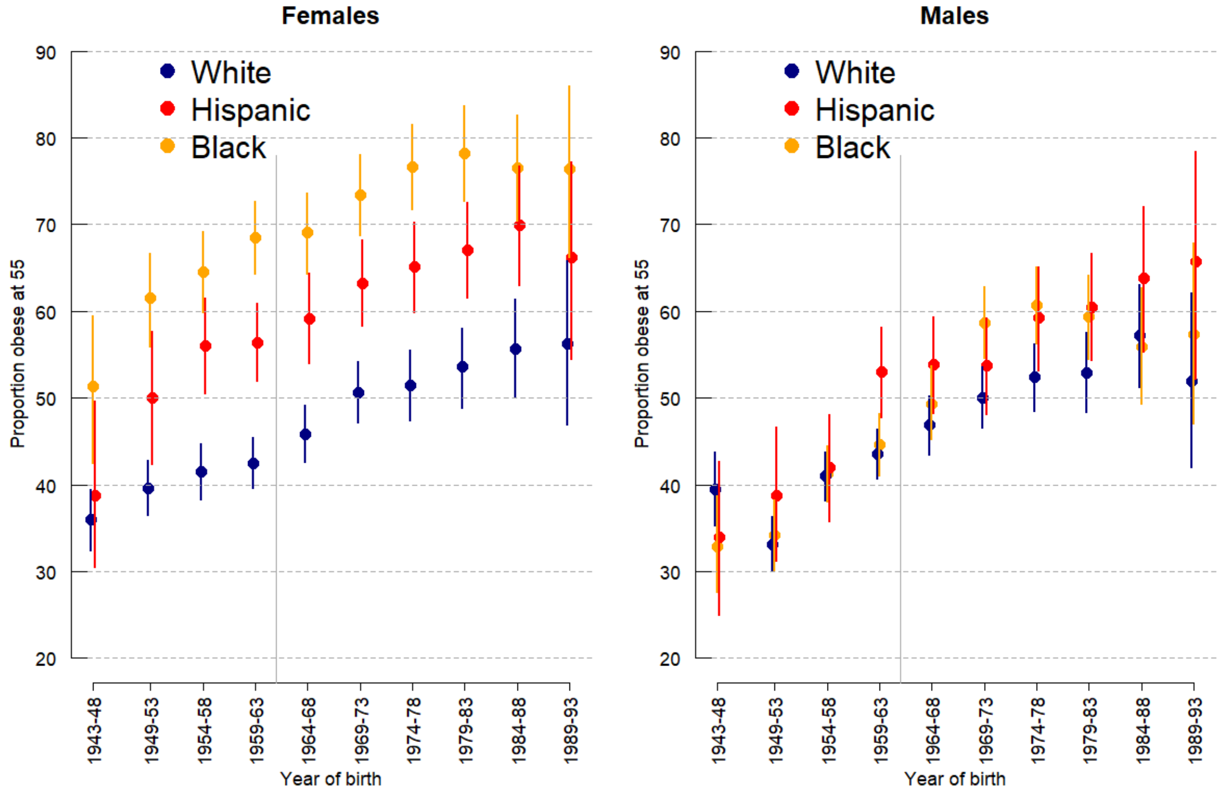


Figure 3. Obesity prevalence at age 55 (with 95% UI) by cohort of birth, sex, and major race/ethnicity.

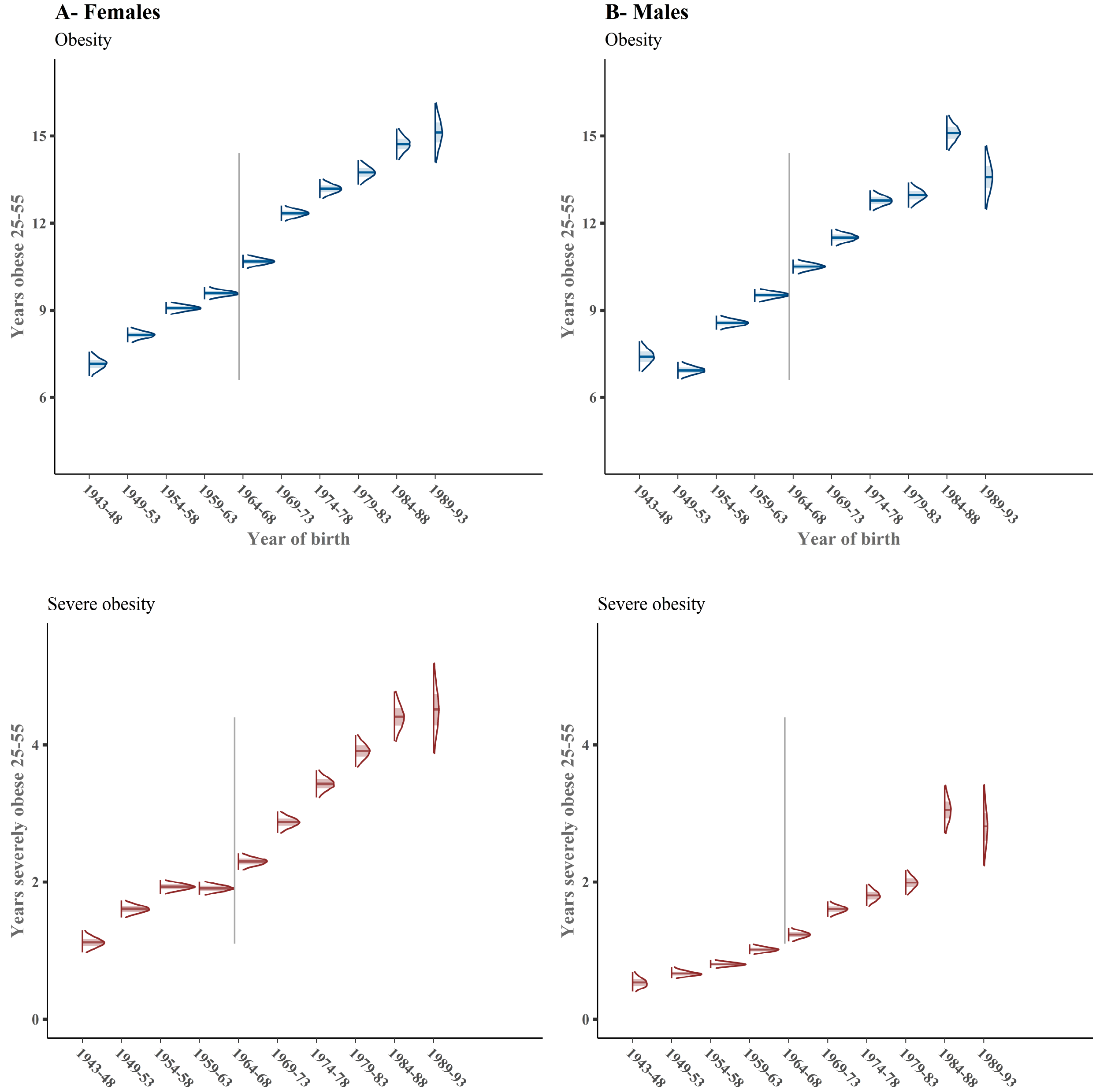


Figure 4. Average fraction of adulthood spent being obese by age 55.

The shaded regions are 50% UIs; the outer regions are 95% UIs.