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Research Article

Projection of US adult obesity trends based on individual BMI trajectories

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Abstract

BACKGROUND
Adult obesity has been increasing in the United States since the 1980s. Its future prevalence will be a key determinant for public health. For the cohorts now in young adulthood, the future prevalence of obesity will depend on current prevalence and future increase in weight.

METHODS
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). We analyzed participants examined between ages 25 and 55 in the years 1998–2018. We applied a functional data analysis technique to probabilistically reconstruct individual BMI trajectories in order to investigate the future prevalence of obesity and severe obesity at age 55, and the mean time spent being obese and severely obese between ages 25 and 55.

RESULTS
We found that the prevalence of obesity at age 55 is expected to reach 58% (95% 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 1964–1968 cohort to 14.7 years (95% UI, 14.2–15.3 years) in the 1984–1988 birth cohort.

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CONCLUSIONS
Although obesity prevalence may level off in the coming decades, higher prevalence of severe obesity and longer durations of obesity are expected to increase the population burden of this disease.

CONTRIBUTION
Prior research has suggested that prevalence of obesity may level off in the United States. Using innovative functional data analysis methods to probabilistically forecast future obesity, we find that severe obesity and years lived obese will continue to increase. Even if the prevalence of obesity stabilizes, the overall burden of obesity may continue to increase.

1. 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 $\geq$ 20) in the United States since the 1980s, from 15% in 1976–1980 to 42.5% in 2017–2018 (Flegal et al. 1998; Hales et al. 2020). Obesity is a risk factor for many major chronic diseases, notably type 2 diabetes (Kahn, Hull, and Utzschneider 2006), cardiovascular diseases (Van Gaal, Mertens, and De Block 2006; Ortega, Lavie, and Blair 2016), and selected types of cancers (Pearson-Stuttard et al. 2018). Accordingly, obesity is associated with all-cause mortality (Prospective Studies Collaboration 2009; Berrington de Gonzales et al. 2010).

Obesity has been argued to be one of the most important contributors to slow health improvements in the United States in recent decades (Preston, Vierboom, and Stokes 2018) and is expected to continue to exert a strong influence on US life expectancy (Olshansky et al. 2005; Preston et al. 2014). 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. For example, it has been shown that duration of obesity (Abdullah et al. 2011), maximum BMI ever attained (Stokes and Preston 2016), and weight change (Myrskylä and Chang 2009) are associated with changes in the risk of death.

Making accurate predictions of trends in several dimensions of obesity is crucial to assessing the future burden of the obesity epidemic. This goal can only be achieved by using already available information 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 (Ruhm 2007; Stewart, Cutler, and Rosen 2009; Wang et al. 2008). 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 predicts weight at any subsequent age. In other words, BMI is highly correlated over the life course.

Because of the strong correlation of BMI over the life course, integrating already observed cohort histories of obesity is 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 (Preston et al. 2014). 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, the Markov property has been an important assumption of the methods that account for cohort effects: The probability of being obese at a future point in time is assumed to depend only on current obesity status. In reality, the trajectory up to the current observation may carry useful information. For example, having been obese for decades versus having become obese recently, despite identical current BMIs, may lead to different future weights: this dependance of the future on the past, even conditional on the present, violates the Markov assumption. Finally, analyses that account for BMI histories have often relied on reported past weights without investigating recall bias (Preston et al. 2014; Stokes and Preston 2016).

A recent study by Ward et al. incorporated individual-level BMI data to construct projections for children (Ward et al. 2017). 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. 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 measures of interest.

Focusing on the cohorts born between 1943 and 1993, we investigate four outcomes: 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. Measures that include information on obesity histories, such as time spent obese, are more comprehensive health measures than obesity prevalence only (Abdullah et al. 2011; Preston, Mehta, and Stokes 2013; Stokes and Preston 2016), and may more accurately reflect the future consequences of the obesity epidemic for disease incidence.

2. Methods

2.1 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 (NCHS 2020). 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). Thus, though NHANES is not a longitudinal study following people over time, it does enable the investigation of how the weight of its participants has changed over time.

While three national surveys were conducted between 1971 and 1994 – NHANES I (1971–1975), II (1976–1980), and III (1988–1994) – data has been collected on a continuous basis since 1999 (‘continuous NHANES’ phase) and has been released since then in two-year cycles. Our analysis pools together all available cycles of the continuous NHANES phase (1999–2018). The dataset analyzed includes 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).

2.2 Correction for misreporting of past weights

NHANES provides both measured and reported current heights and weights for all individuals. Since it is well known that height and weight are often misreported (Flegal, Kit, and Graubard 2018; Palta et al. 1982; Ward et al. 2016) we computed all of the BMIs using the individual’s measured height. For the current BMI we used the individual’s measured weight for the same reason. For the three series of past BMIs (1 year before, 10 years before, at age 25) we had to rely on weights as reported by NHANES participants. One critical question is thus the extent to which NHANES participants misreported past weights. If misreporting of distant weights is significant, i.e., if those in middle age tend to exaggerate how lean they were in their youth, age-related weight-gain will be overstated, and hence likely future weight gains for today's young adults overestimated.

Assuming that those who misreport their current weight are also more likely to misreport their past weight, we corrected each individual's past BMIs (1 year before, 10 years before, at age 25) 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 underreport more their current weight. In what follows, reported past BMIs refers to these corrected reported past BMIs.

Since NHANES does not follow the same individuals from wave to wave, even after this first correction we had to abandon the individual level and turn to means at the cohort level to assess whether a bias existed for reported past BMIs. Specifically, we compared mean BMIs estimated using reported past weights and using weights measured during NHANES II (1976–1980), NHANES III (1988–1994), and continuous NHANES. For example, two sets of BMIs may be used to estimate mean BMI at age 30 for the 1960 birth cohort: BMI 10 years before survey based on weights reported in 2000 by members of this birth cohort, and weights actually measured in 1990, during NHANES II. This enables the assessment of whether past BMIs are biased, since their mean value can be compared to that actually measured at previous waves: though they are based on two different sets of individuals, the two sample means estimate the same quantity. The regions of the age-cohort plane in which mean-measured and reported BMIs 1 and 10 years before survey could be compared are given in Figure A-1. Running separate analyses for males and females, we indeed found evidence of misreporting specific to past weights. Most notably, for women, the mean BMI surface estimated using BMI 10 years before survey was systematically below the surface estimated using measured BMIs (Figure A-2). In other words, women underestimate more their weight 10 years before survey than they misreport their current weight. If not corrected, this would have overestimated the pace of weight gain in individuals, which might have led to overestimates of future prevalence of obesity.

For each sex, we therefore constructed a second set of corrected reported 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. Details of mean corrections applied to reported past BMIs can be found in Table A-1. The proportion of observations above 30 kg/m^2 for each BMI series (uncorrected, first correction, second correction) is given in Table A-2.

2.3 Functional data analysis

Our aim is to reconstruct BMI trajectories at the individual level for individuals included in NHANES, and then to assess how population-level metrics (e.g., obesity prevalence at a given age) will change in the future using these reconstructed curves. In non-technical terms the approach looks as follows. We take as the starting point the reporting-error-corrected observations of each individual's weight and height measures. These data points provide empirical data to determine how weight and BMI evolve over age (we assume height to be constant). At the level of observables, the approach is necessarily backwards-looking. However, by combining information on current weights and information on how weight changes with age, we can get insights into the future. Assume that person A is observed from age 25 to 35, and that person B is observed from age 25 to 50. Person A's trajectory to 35 evidently contains much information on person A's trajectory after 35. But person B's trajectory also informs person A's trajectory after 35, since it informs on how people generally gain weight after 35. Using both trajectories thus clearly helps predict person A's future trajectory to age 50, and once such individual trajectories are projected into the future, they can be aggregated into population-level measures of obesity.

The key challenge in the process is how exactly to reconstruct an individual trajectory effectively using all the information available (the part that has been observed, combined with other individual trajectories). One extremely flexible curve reconstruction technique is based on Gaussian processes (GPs). The basic logic behind functional data analysis using GPs is simple. Just as a random variable can be seen as a mechanism that generates numbers, a GP can be seen as a mechanism that generates functions. In our case, this refers to the functions that map age on BMI for individuals in the sample. Exactly as a multivariate normal distribution is determined by its mean vector and its correlation matrix, a GP is governed by its mean and covariance functions. In particular, the covariance function controls correlation between values at nearby locations and thus determines how smooth the functions that are generated will be. In our application, these correlations govern the smoothness of weight change (mostly weight gain) over the life course of individuals.

The one key trick that has made Gaussian processes popular is that assuming a given, partially observed function can be modeled as the realization of a GP, it is easy to express how our knowing the function's value at the specific locations we observed reduces uncertainty in the function's value at any other location. In other words, knowing the mean and covariance functions of the GP and which values were realized at a given set of locations (in our case, the BMI of the individual at the specific ages NHANES informs on), we can update our belief in the function's value at any other point (that is, on the individual's BMI at any age, in particular not-yet-observed future ages). When the mean and covariance functions of the GP cannot be assumed to be known, one can place priors on them and proceed in the same way. And just as a random variable can be used to represent uncertainty in the value taken by some parameter, a Gaussian process can be used to place a prior distribution on functions – for instance, on the mean function of a Gaussian process.

In each of the strata defined below, we applied a recently developed Bayesian hierarchical model for the smoothing of functional data using GP methods (Yang et al. 2016). 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.

Since we expected weight gain over time to differ between sub-populations, 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).

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).

2.4 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.

2.5 Sensitivity analyses

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

Curve reconstruction was performed using the MATLAB toolbox BFDA (Yang and Ren 2019). All other analyses were conducted using R (R Core Team 2020). NHANES data are freely available at https://wwwn.cdc.gov/nchs/nhanes/. All computer codes used to generate the results reported in this study are available at https://github.com/nptodd/bmi.

3. Results

3.1 Characteristics of participants analyzed

Table 1 presents summary characteristics of the N = 26,337 NHANES 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: current obesity prevalence in young adults cannot simply be taken as a prediction of future prevalence in these cohorts, but must also account for likely future weight gain. Furthermore, though they illustrate important and well-known characteristics of the US population (such as its ethnic composition and its high obesity burden), figures in Table 1 also hide important historical trends in the composition of the birth cohorts analyzed; e.g., declining prevalence of smoking (Figure A-3), increasing size of the Hispanic group (Figure A-4), and rising educational attainment among females (Figure A-5). The continuation of smoking was found to be highly predicted by smoking at age 25, our measure of smoking status (Figure A-6).

Table 1: Characteristics of participants analyzed

	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 graduate	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)

Note: 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 = 7 pregnant women interviewed at other cycles.

3.2 Individual-level trajectories between ages 25 and 55

Figure 1a plots the BMI curves of selected members of the same stratum who were interviewed by NHANES at different ages. The figure illustrates 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. The reason why we predict (with considerable uncertainty) that the fourth individual (lower right panel) will cross the $40kg/m^2$ threshold (turning severely obese) in the future is both because her current BMI, observed at ages below 30, is high and because individuals tend to gain weight in their 30s and 40s, as illustrated by individual 1 (top left panel) and to a lesser extent by individual 2 (top right panel).

3.3 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 example strata, that of non-smokers with the lowest educational attainment (high school or less). Although starting with similar values of mean BMI at age 25, weight gain with age was found to be accelerated among non-Hispanic Black women compared to non-Hispanic White and Hispanic women, resulting in large differences in mean BMI at age 55 (Figure 1b, left panel). Converting back to weights may help appreciate these differences in concrete terms: for instance, the maximum difference of 10 points in the mean BMI at 55 that is attained in females in Figure 1b corresponds to a weight difference of about 30 kg for individuals 170cm tall. By contrast, little evidence could be found that the pace of weight gain varied by race/ethnicity in men in our selected strata (Figure 1b, right panel).

Figure 1: Example reconstructions of BMI trajectories

a) Individual-level reconstruction of BMI trajectories

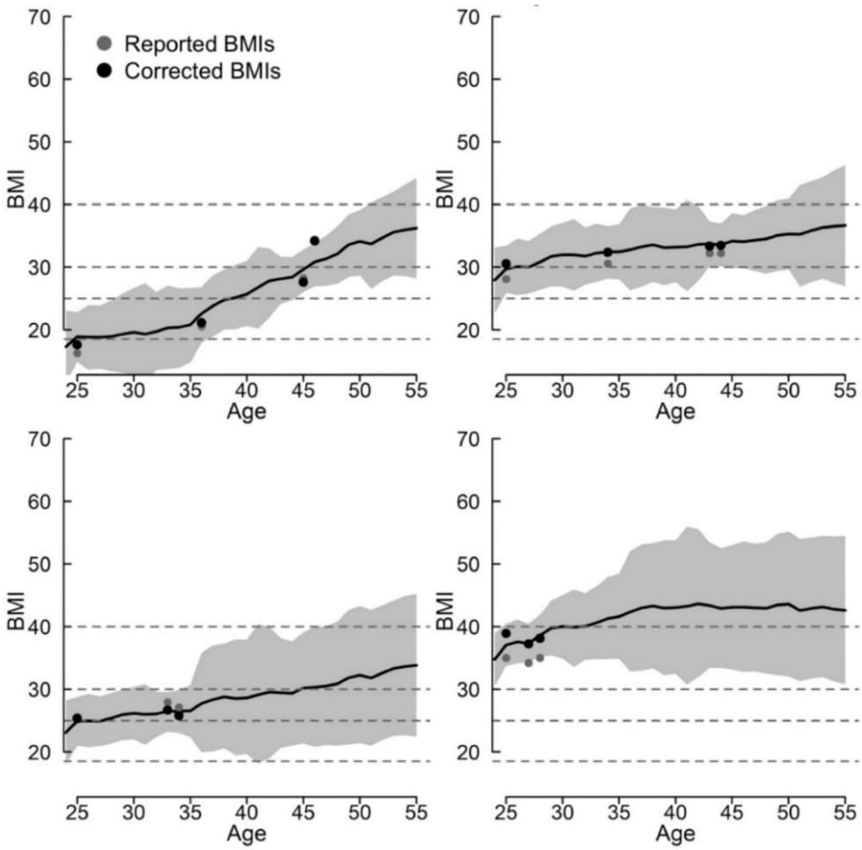
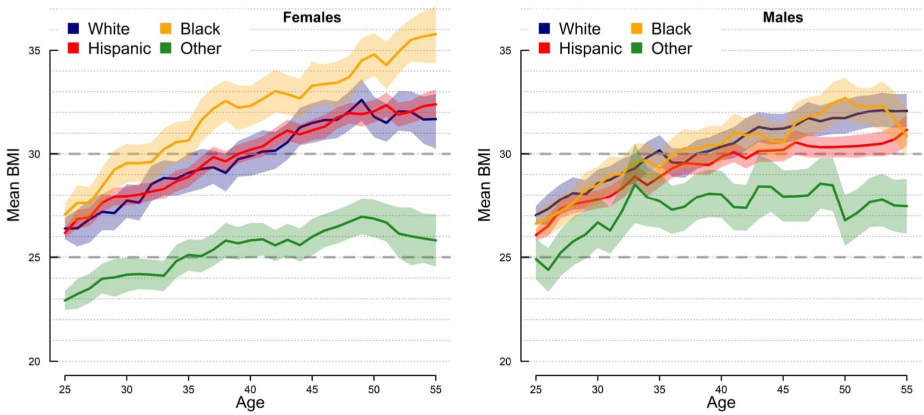


Figure 1: (Continued)

b) Group-level trajectory for selected strata



Note: The four figures of Panel A separately show the BMI trajectory (average posterior and 95% uncertainty interval [UI]) of selected NHANES participants. All four selected individuals belong to the same stratum (Black non-smoking females with the lowest educational attainment) but were interviewed at different ages by NHANES. BMIs based on uncorrected reported weights are shown in gray ('reported BMIs'). BMIs corrected for misreporting, which are used in the analysis, are shown in black ('corrected BMIs'). 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 by 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 Figure A-7 in the Supplement for the average posterior of the mean BMI function for all strata.

Among both males and females, the 'other' race group, which includes Asian Americans, showed markedly lower mean BMI values across the age span investigated. The results for all strata (shown in Figure A-7 in the Supplement) highlight several observations. While BMI gain with age was found to be universal and unequivocal, leading from a mean BMI at age 25 close to mild overweight to a mean BMI at age 55 close to the threshold for obesity for a majority of strata, large differences in starting levels and pace of BMI gain were found between some strata. For instance, pronounced differences for mean BMI at 25 were generally found in females according to race/ethnicity. Such differences according to race/ethnicity were much less evident in males. The curves of Hispanic and non-Hispanic Whites were generally found to be close in all sex–education–smoking combinations.

3.4 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 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 (Figure A-8) and was also observed when older cohorts were removed from the analysis (Figure A-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. High uncertainty for cohorts that are still in early adulthood derives from high uncertainty in individual trajectories for members of these cohorts, an uncertainty that highlights the fact that the model does not rely on so strong a set of assumptions as to produce unrealistically narrow confidence intervals for cohorts of which little is yet known.

3.5 Severe obesity prevalence at age 55

Obese status hides a large diversity of conditions, from milder obesity to more extreme situations. Turning to severe obesity (BMI > 40) at age 55 (Figure 2, lower panels), the model predicts that it will increase rapidly among females, from 9.0% (95% UI, 7.8%–10.3%) in the 1959–1963 cohort to 16.0% (95% UI, 13.5%–18.6%) for those born in 1984–1988. 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 1984–1988 birth cohort.

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

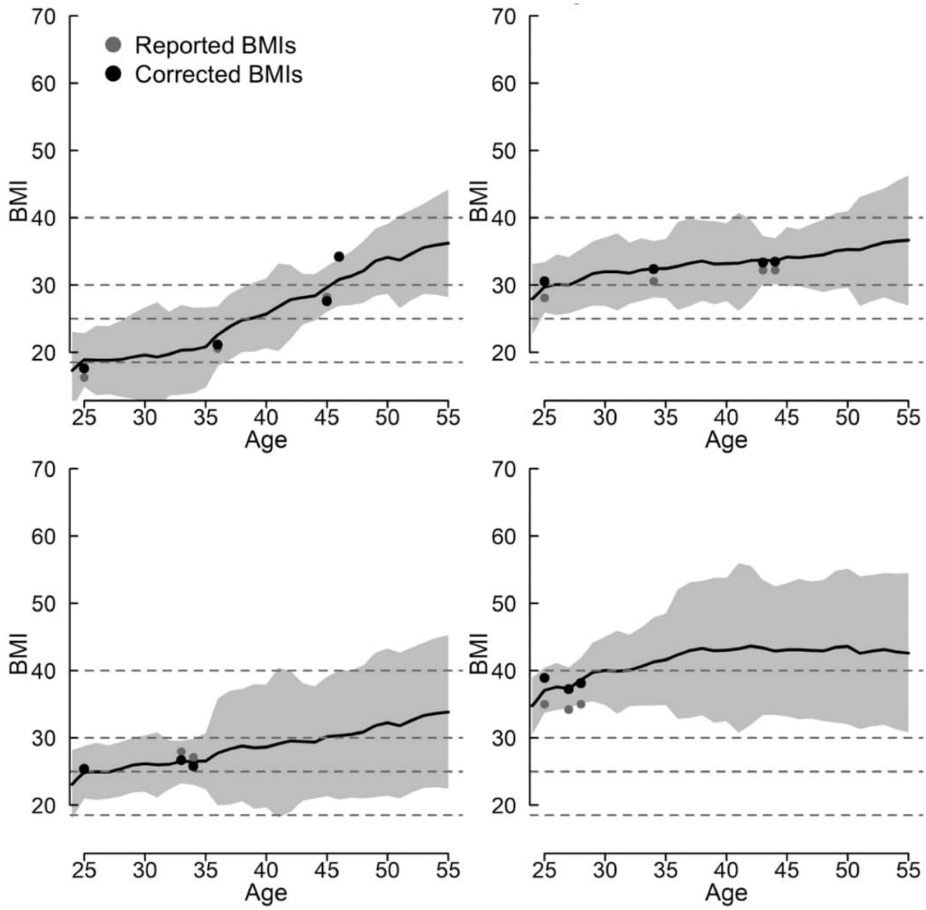
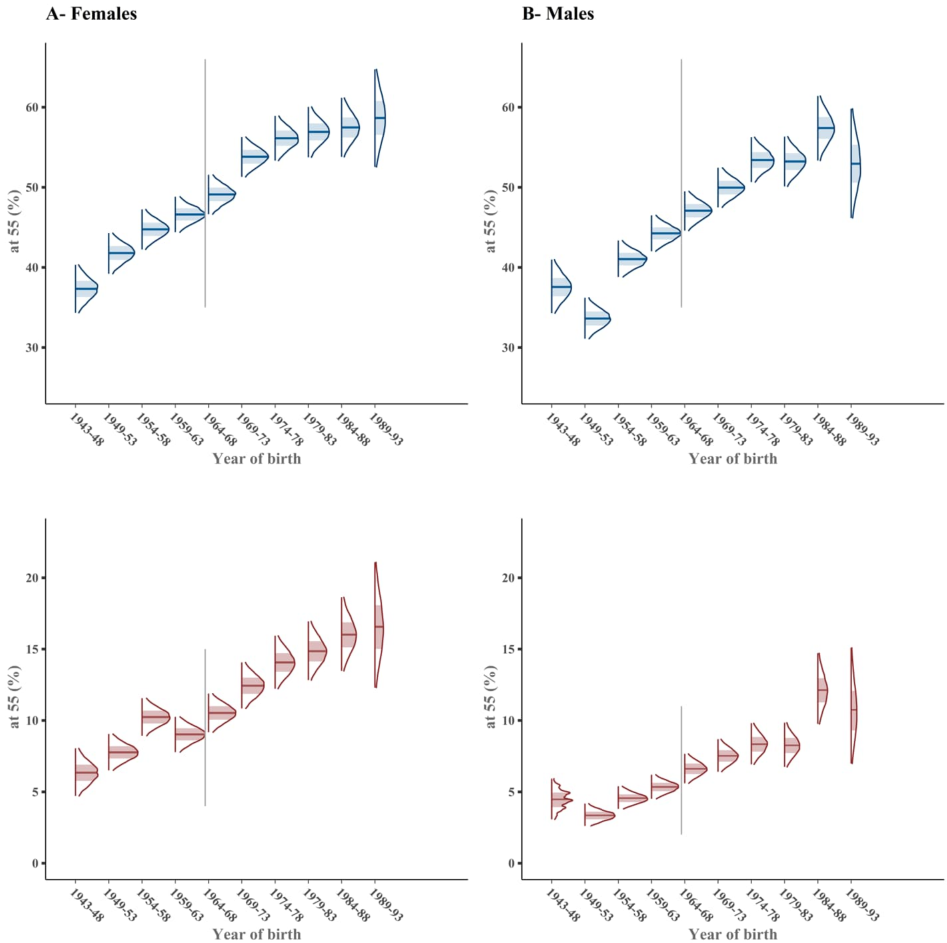


Figure 2: (Continued)

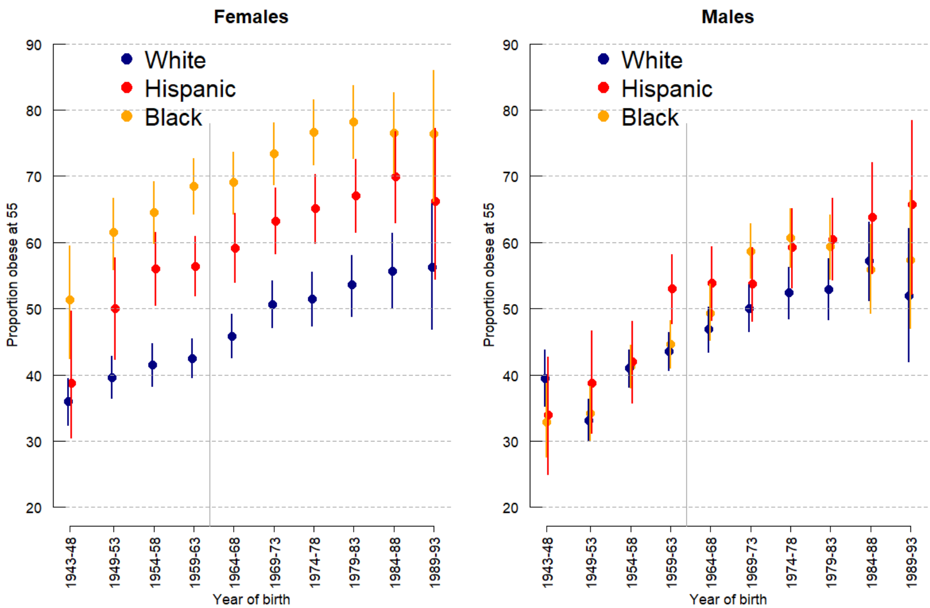


Note: The top panels show obesity prevalence at age 55 by birth cohort, for females and males separately; similarly, the lower panels show severe obesity (BMI > 40) prevalence at age 55. On each plot, a vertical line separates retrospective estimates (estimates for cohorts who have already attained age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

3.6 Heterogeneity by race/ethnicity

Large differences were found in the projection by race/ethnicity, in particular among women (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. While the point estimates differ by 25 percentage points among women, among men the race/ethnicity differences were markedly smaller. The lowest obesity prevalence is predicted to be among non-Hispanic White men, at just above 50%, and highest among Hispanic men, with roughly 15 percentage points higher prevalence.

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

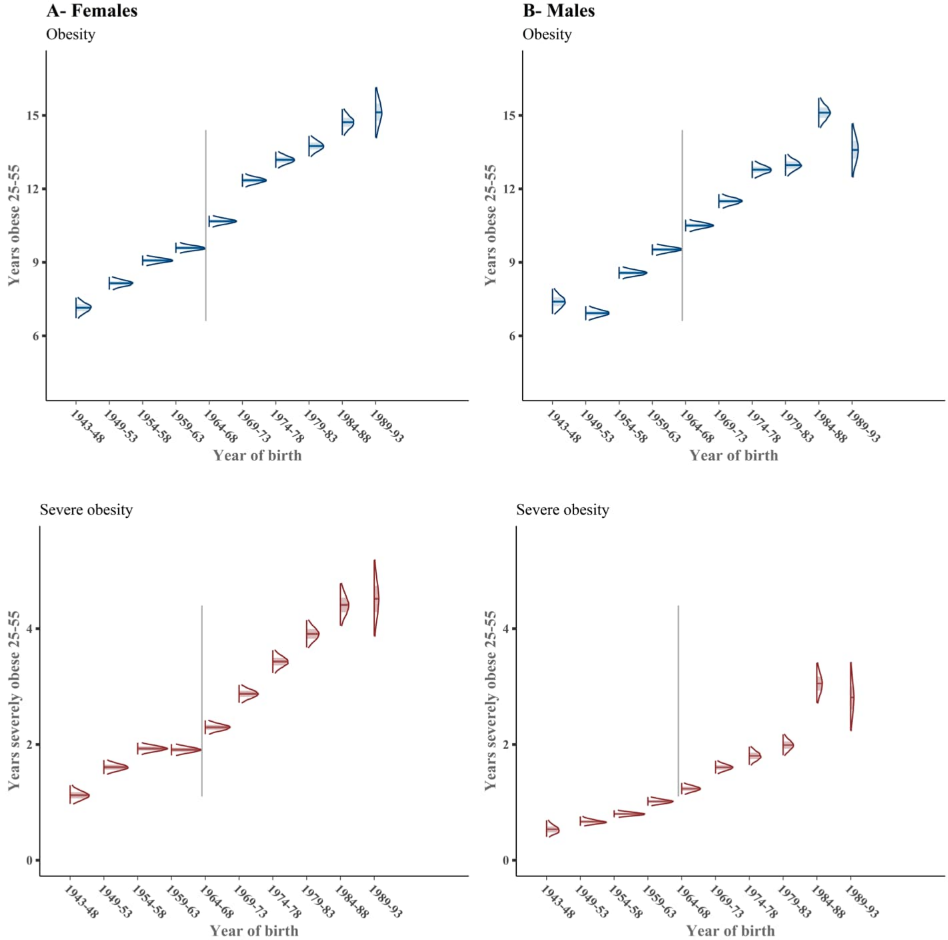


3.7 Time spent being obese by age 55

As previously mentioned, prevalence is certainly less relevant than quantities that actually register the cumulative health damages brought about by obesity. One simple cumulative obesity metric is time spent obese between two given ages. 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 1984–1988 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 1984–1988) 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 1964–1968 cohort. The patterns for men closely mirror those of women.

The same increasing 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). This is in sharp contrast to the deceleration that is predicted for obesity prevalence, and likely reflects more accurately how the health consequences of obesity will evolve in the near future.

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



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

4. 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 (Ogden et al. 2015, 2016). The examination of measures of obesity other than 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 20s, half of non-Hispanic White women, but 4 out of 5 non-Hispanic Black women, will be obese at age 55.

Comparison of our estimates to the main body of obesity projection literature is not straightforward. Part of the challenge is that comparable projections are often based only on projection of obesity prevalence, whereas we project the full BMI distribution including years spent in various BMI states, and part of the challenge stems from the fact that often the projections are not probabilistic. Preston et al. (2014) provide a helpful 3-category classification of obesity forecasting approaches: extrapolation of prevalence (Ruhm 2007; Wang et al. 2008), extrapolation of covariates linked to obesity (Finkelstein et al. 2012), and Markov modeling of the transitions of BMI states (Preston et al. 2014). We add to this list the approach of constructing individual BMI trajectories and aggregating over individual trajectories. This approach has been used, for example, by Ward et al. (2019), in addition to this current paper.

Each of these approaches have their strengths and weaknesses, and the projected obesity levels may differ from our results for many reasons. The approach to extrapolating obesity is transparent but perhaps overly simplistic, and possibly because of the simplicity of the extrapolation approach our estimation of future obesity prevalence seems more optimistic than what extrapolation delivers. Our levelling-off obesity prevalence at age 55 (Figure 2) contrasts sharply with the results of a much-cited work based on linear extrapolative regression, which predicted obesity prevalence in adults would reach about 65% in 2050 and 100% by 2100 (Wang et al. 2008). This is clearly due to the unrealistic assumption at the core of linear regression, namely a constant yearly rate of increase.

Finkelstein et al. (2012) use an approach of predicting the predictors of obesity, and thereby constructing future obesity estimates. The time span covers approximately two decades up to 2030, and the results suggest that within this time window, obesity and severe obesity over all adult ages (18 years and above) will increase in the United States by one third and by 130%, respectively. The uncertainty associated with such an approach, based on predictions of covariates, is difficult to quantify. The point estimates, however, appear to be markedly higher than our median estimates.

Preston et al. (2014) use a Markov Chain approach to forecast prevalence of obesity and morbid obesity (BMI ≥ 35.0) until the year 2040. The results suggest deceleration in the increase of obesity, such that 51% of women and 47% of men aged 25 to 84 are projected to be obese by the end of the forecasting window. The approach uses reporting-corrected weights, similar to our study, but categorizes the data into BMI categories before analysis, thereby losing information, and assumes that future transitions do not depend on the past trajectory. Direct comparison of our results and those of Preston et al. is challenging because of the different age groups involved (Preston et al. also use very young ages in the estimate of the prevalence) and of differences in BMI categories (we use severe obesity defined as BMI 40 or above). However, both our results and those of Preston et al. (2014) point towards clear deceleration in the increase of obesity prevalence, and more continued increase in severe or morbid obesity categories.

Our findings are also somewhat more optimistic than the results of more sophisticated projection methods: 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 predict 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 that 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 (Ward et al. 2019).

Because obesity will continue to be one of the most important determinants of health trends in the United States 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 tackle the problem of misreporting of past weights and directly address 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. In particular, this approach suppresses strange inconsistencies found with previous methods; e.g., between total and sex-specific obesity prevalence (Wang et al. 2008).

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 measure such as obesity prevalence among all adults cannot be estimated without additional assumptions being made about the cohorts who are currently in childhood. Another limitation resulting from focusing on cohorts already in adulthood is that it severely complicates the comparison of our results with that of other methods, such as those projecting obesity prevalence for all adults (Wang et al. 2008). In addition, we assume that individuals with identical observed BMI trajectories will follow similar BMI paths at older ages, irrespective of birth cohort. This implicitly assumes that conditional on early adulthood BMI, changes in the obesogenic environment from one cohort to the next may be ignored. Finally, any large-scale, rapid, effective, pharmaceutical or non-pharmaceutical treatment of obesity would radically change the obesity landscape and would likely cause future trends to deviate from any currently conceivable projection.

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 of obese people’s increased susceptibility 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. An accurate assessment of the future burden of obesity requires us to move beyond the focus on obesity prevalence.

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Data access

NHANES data are freely available at https://wwwn.cdc.gov/nchs/nhanes/. All computer codes used to generate the results reported in this study are available at: https://github.com/nptodd/bmi.

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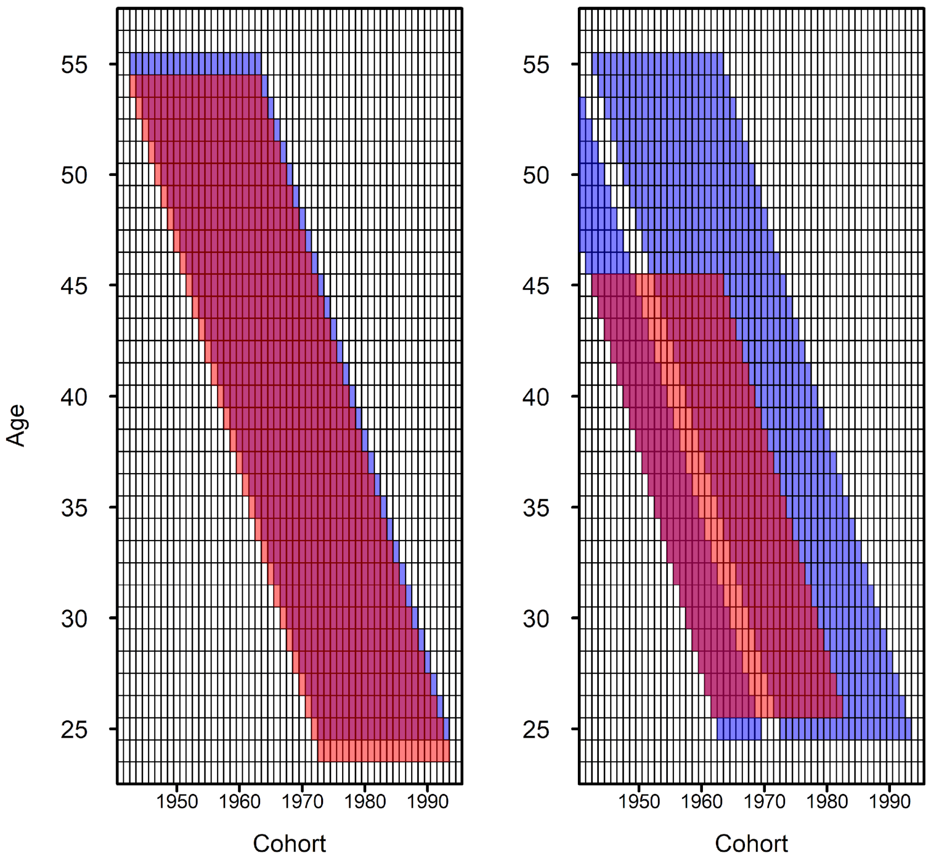
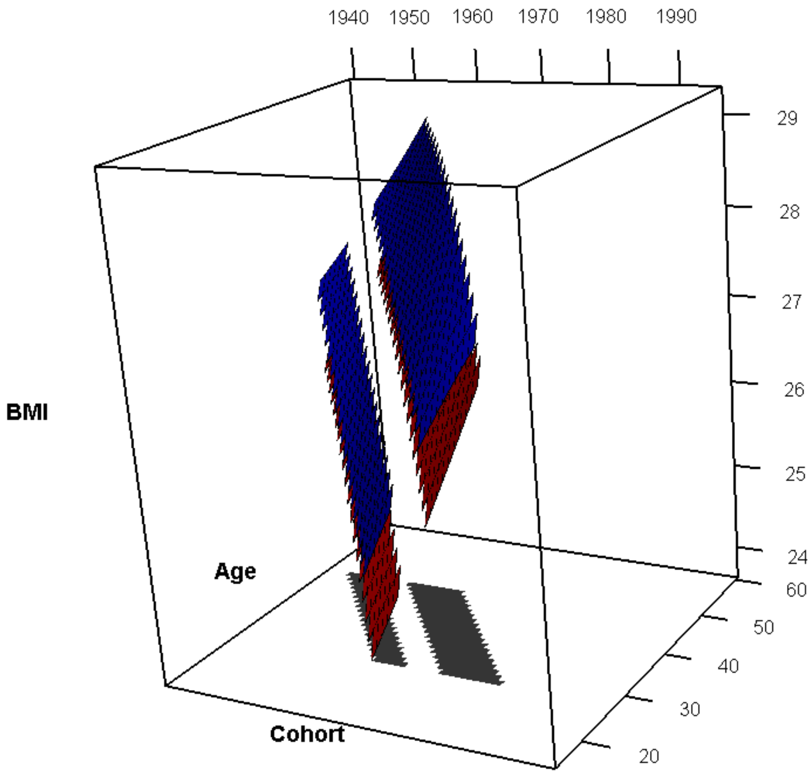
Appendix

Figure A-1: Domains of the age-cohort plane where average BMI can be estimated using measured BMIs (blue) and reported past BMIs (red)



Note: 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 years 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).

Figure A-2: Mean female BMI surface, estimated using either measured BMI (blue) or reported BMI 10 years before survey after first correction (red)



Note: In each case, the BMI surface was estimated with a Generalized Additive Model with a Gamma distribution, using survey weights for unbiasedness.

Table A-1: Mean (SD) bias of current reported BMI, and mean correction (SD) applied to reported past BMIs

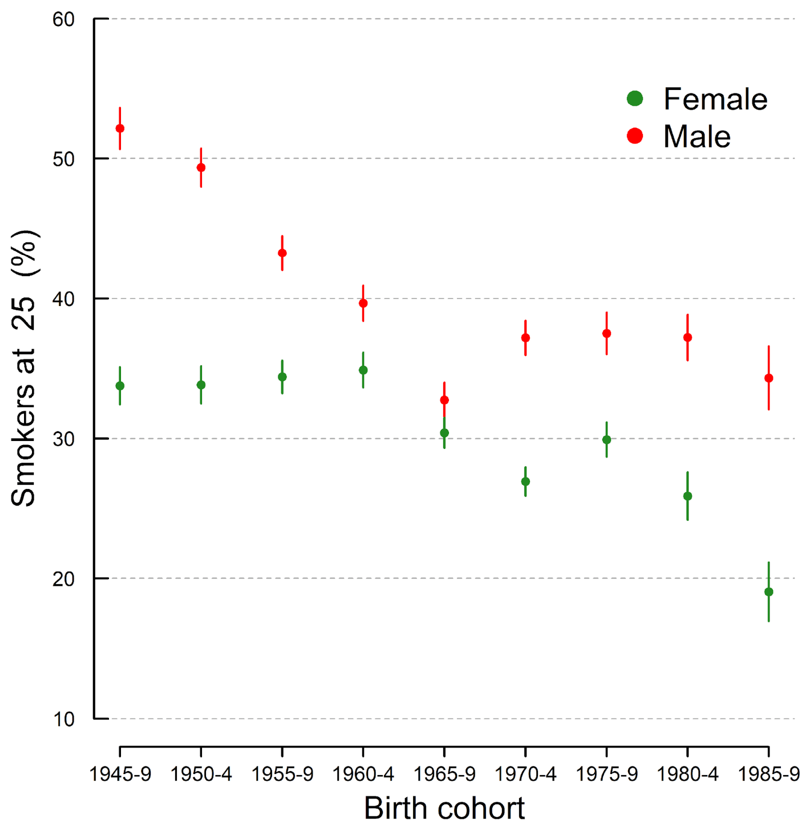
	Bias of current reported BMI	Global correction for BMI		
		1y before survey	10y before survey	at 25
Females	0.52 (1.70)	0.45 (1.68)	1.17 (1.68)	1.45 (1.72)
Males	0.04 (1.62)	–0.17 (1.61)	0.11 (1.52)	0.26 (1.56)

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

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

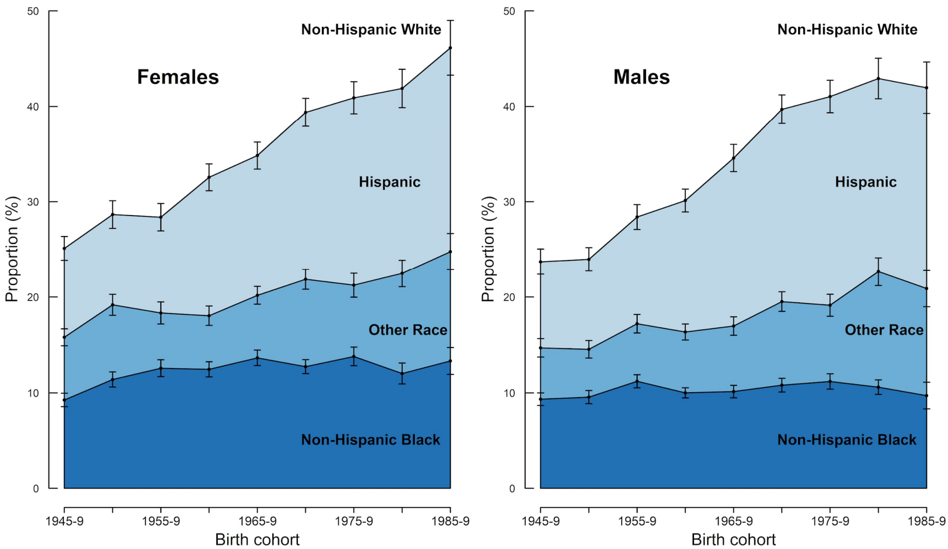
	Uncorrected	First correction	Second correction
Current BMIs	35.1%	36.7%	–
BMIs 1y before survey	34.7%	36.2%	35.5%
BMIs 10y before survey	22.6%	24.5%	26.1%
BMIs at 25	13.2%	15.0%	16.6%

Figure A-3: Proportion smoking at age 25, by birth cohort and sex



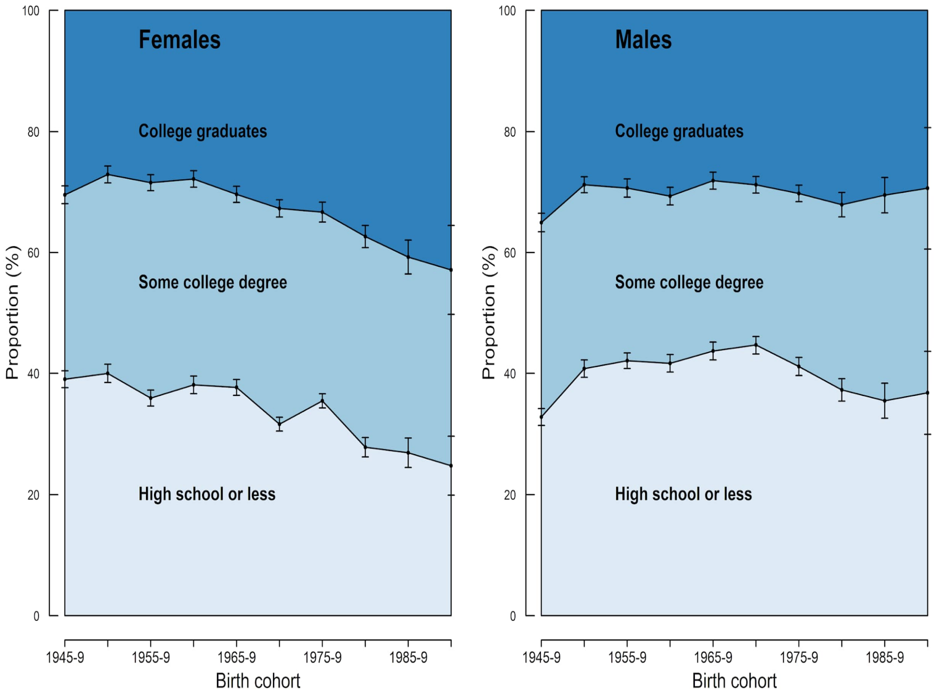
Note: Proportions ± s.e.

Figure A-4: Ethnic composition of birth cohorts, by sex



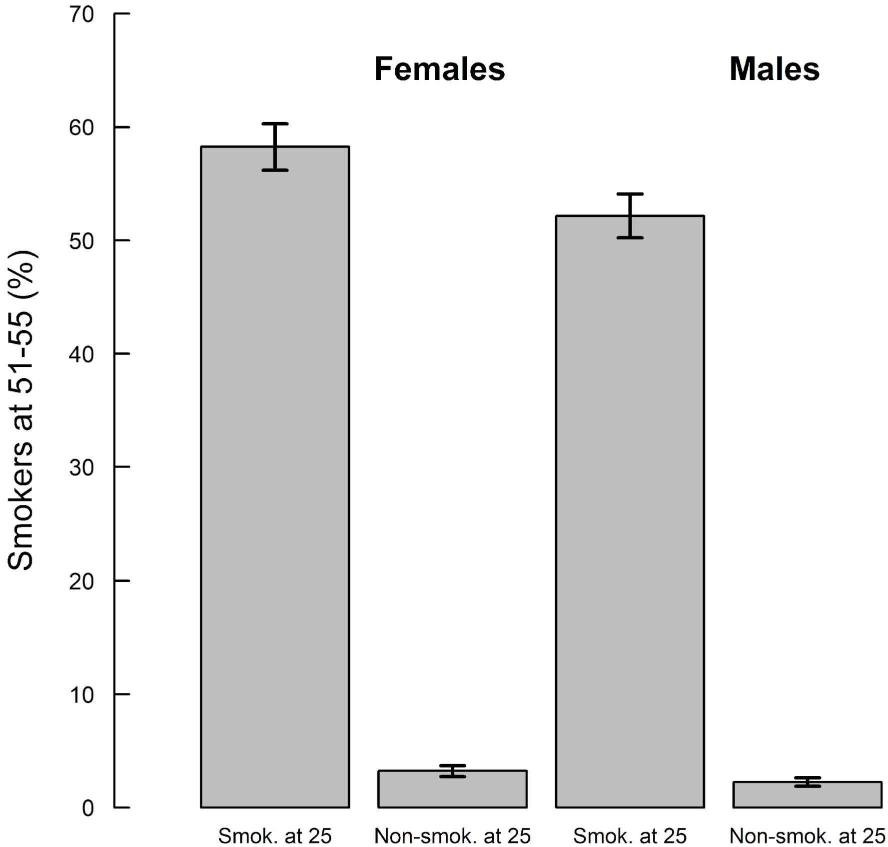
Note: Data: individuals 25 years and older at NHANES interview.
Proportions ± s.e..

Figure A-5: Educational attainment by birth cohort and sex



Note: Data: individuals 25 years and older at NHANES interview.
Proportions ± s.e.

Figure A-6: Probability of smoking at ages 51–55 according to smoking status at age 25 and sex



Note: Data: individuals aged 51–55 at continuous NHANES interview.
Proportion ± standard error (s.e.).

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

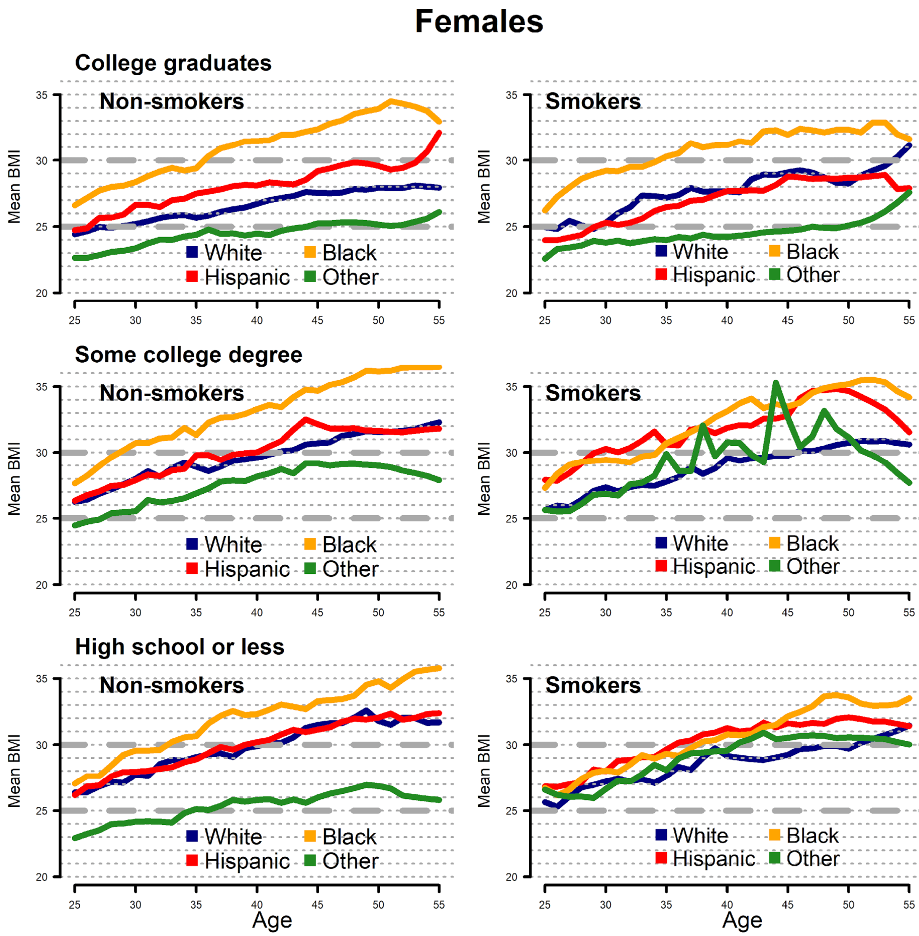


Figure A-7: (Continued)

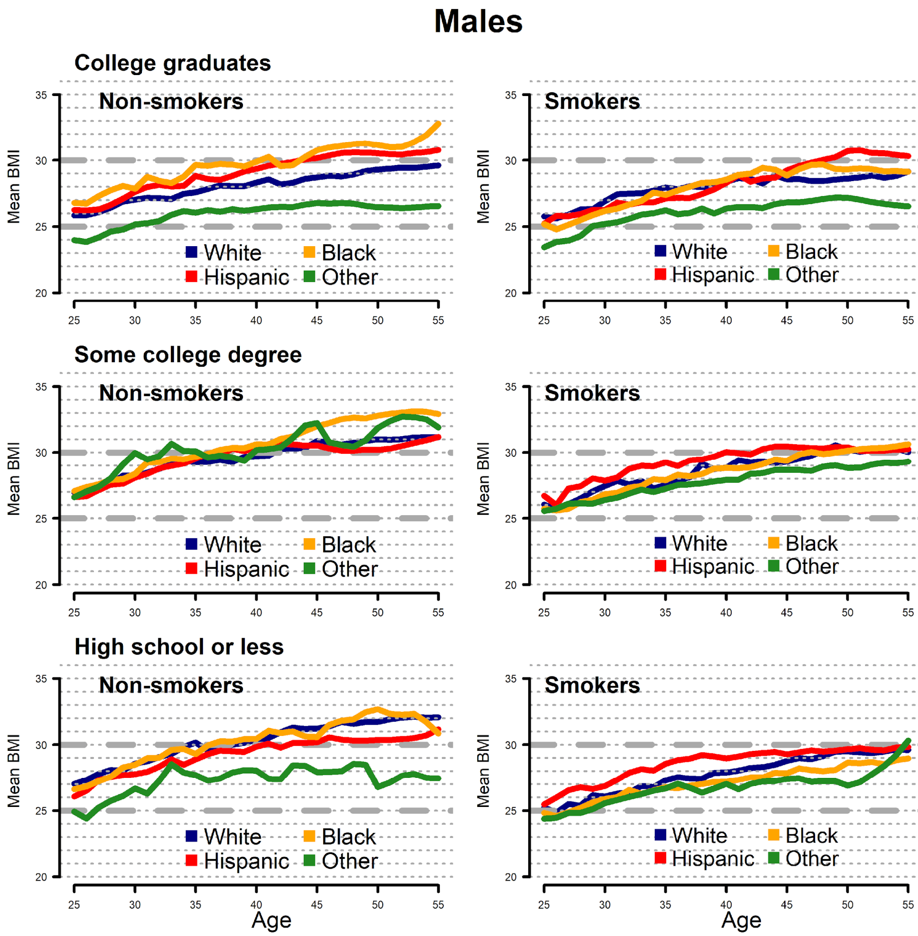
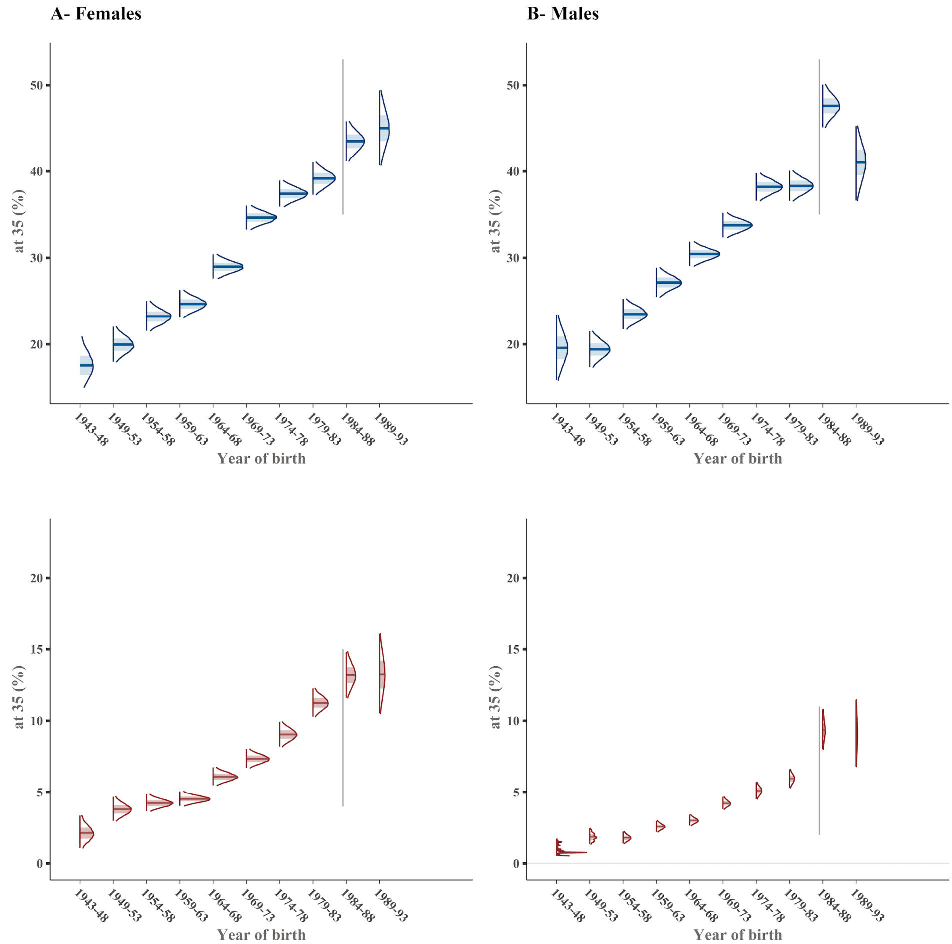


Figure A-8: Obesity and severe obesity at age 35, by sex



Note: 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.

Figure A-9: Obesity and severe obesity at age 55, by sex, with older cohorts (1943–1954) removed from the dataset